Social network analysis in agricultural economics: progress, challenges and prospects of an integrated methodology

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Abstract

Purpose – The purpose of this review is to demonstrate to what extent the method of social network analysis (SNA) has been integrated into agricultural economics and how it has reformed the characterization and utilization of interpersonal interactions in agricultural decision-making.

Design/methodology/approach – Through the lens of network information diffusion and aggregation mechanisms, this study describes the typical macro- and micro-network structures incorporated in social network models and establishes a mapping to identify the key structural elements that characterize these channels. This study then performs a meta-analysis of publications in top field journals during the past 2 decades to unveil four major thematic groups. In each thematic group, this study provides an in-depth review of the integration between SNA and the conventional empirical approach in data collection, identification and interpretation. Achievements and limitations of the current literature are finally discussed to provide future directions to promote the integration of SNA in agricultural economics.

Findings – This study shows that the root of social network effects can be characterized by information set changes, and SNA has enabled agricultural economists to capture such changes with unique data collection, modeling and identification tools.

Originality/value – This paper reveals the latest methodological progress that embeds SNA over the empirical course of agricultural economic studies and extends the scope of interpersonal social networks to those of firms, organizations and trading partners.

Keywords Social network analysis (SNA), Resource allocation, Knowledge and risk sharing, Technology adoption, Organization and trade

Paper type Research article

1. Introduction

Information sets lie at the core of individual behaviors. Information flows among people could thus result in interdependent behaviors. Due to the lack of public channels, social networks play a vital role in the information exchange among producers and consumers of agricultural

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goods, especially in developing countries (Breza *et al.*, 2019). Understanding the relationship between social networks and behavioral interdependency therefore lays the foundation for designing network-based policies that enhance information exchange and promote desired behaviors (Beaman *et al.*, 2021). With a highlight of the effect on information sets of decision-makers through two fundamental channels, i.e. information aggregation and information diffusion, social network analysis (SNA) provides an essential toolbox to analyze behavioral interactions among agents and entities, from the perspective of individual, relational and network-wide characteristics. Based on the integration of econometric approaches, it further reveals underlying drivers of interdependent individual decision-making, which are central to informed policymaking. Compared to early studies through the lens of spillover or peer effects, SNA not only allows for a complete account of heterogeneities and dynamics of the behavioral interdependency, but also offers a set of identification strategies to evaluate network effects precisely.

With a comprehensive review of recent publications in field top journals, this paper examines to what extent SNA has been integrated into agricultural economics, and how it reforms the characterization and utilization of interpersonal decision interactions. We identify macro and micro network structures, and modeling techniques of information exchange that arise from aggregation and diffusion mechanisms, across major thematic groups based on a meta-analysis of the publications. In each thematic group, we conduct an in-depth review of how SNA is embedded in the sampling, empirical modeling, and identification strategies to improve the estimation and understanding of network effects. Implications on effective seeding strategies of agricultural policies are provided. Finally, achievements, limitations and future directions to consolidate the integration of SNA in agricultural economics are discussed.

Our review suggests that the adoption of network properties as instrumental variables enables a more precise disentanglement of confounding effects among peer behaviors, characteristics and unobserved traits, and corrects biased estimates of network effects. Unobserved common characteristics among agents and shared external environmental factors are the two key sources of endogeneity when estimating network peer effects. While the conventional approach is to use lagged peer behaviors as instrumental variables, the exogeneity assumption is often violated as historical peer behaviors may still be correlated with the sources of endogeneity (Carrell and Hoekstra, 2010). Some studies randomly assign agents in experimental environment to ensure the exogeneity of peer effects, but interpersonal interactions in controlled experiments may differ from real-world interactions, thus will limit the external validity of their findings (Jackson, 2014). Compared to these methods, SNA provides an alternative instrumental variable by exploiting local asymmetries in social networks that are reflected in distant peer (i.e. peer's peers) behaviors, which can not only ensure strong exogeneity, but also be applied to large-scale observational studies (Bramoullé *et al.*, 2009). SNA also facilitates the development of network-based Randomized Controlled Trials (RCTs) and alleviates the "reflection problem" in linear-in-means models of social interactions on a more fundamental way (Manski, 1993). Besides, SNA is a more comprehensive and cost-effective approach to collect the network connection data by combining sampling and censusing techniques, compared with the traditional means of random sampling which only captures directly observable connections (Breza *et al.*, 2020). We therefore demonstrate that SNA lays the micro-foundation to systematically characterize heterogeneities and dynamics of interdependent behaviors arising from the individual positions and connections in social networks. Our finding suggests that it is a valuable means to identify opinion leaders in social networks, so effective seeding strategies can be implemented to accelerate information exchange and behavioral changes.

A few recent studies have examined the application of SNA in the general field of economics. Jackson (2014) explored the externality theory that underlies social network effects. Munshi (2014) investigated the role of community networks in social mobility. Chuang and Schechter (2015) focused on the social network effects on health behaviors and technology diffusion. Among the current reviews, the one that is the closest to this paper is

Barnett-Howell and Mobarak (2021). However, their review has weighted relatively more toward the discussion of SNA techniques, whereas this paper shows SNA's integration with conventional empirical approaches and extension of interpersonal social networks to interactions among agricultural firms, organizations, and trading partners.

The paper is organized as follows. Section 2 summarizes key network structural elements in major information aggregation and diffusion models. Section 3 reviews SNA applications in agricultural economics. Section 4 discusses current achievements, limitations, and future directions. Finally, Section 5 concludes the paper.

2. Network structures to model information aggregation and diffusion

2.1 Macro- and micro-network structural elements

SNA primarily focuses on interactions among agents, where individual behaviors are shaped by relational characteristics and network structure. Networks consist of *nodes*, representing individuals or entities, and *edges* as their connections. In particular, when a study focuses on within-group interactions, individuals are considered as nodes while their interactions are considered as edges. In contrast, when inter-group interactions are the focus, groups themselves are nodes and group interactions are edges.

Macro- and micro-network structures affect the information transmission within the network. Macro structures are network-wide properties like connectivity and tightness. Connectivity is measured by the *diameter* (i.e. the longest distance between nodes), *degree distribution* (i.e. the number of nodes across edges), and *average path length* (i.e. the shortest path between nodes). Tightness is measured by *global clustering coefficient* (i.e. the likelihood of connection between nodes that are connected to a third one), and *density* (i.e. the portion of possible connections that are realized).

Microstructures are edge- or node-wise properties. At the edge level, the edge *weight* represents connection intensity like contact frequencies, while *tie strength* captures the presence of different types of connections like being both neighbors and church mates. At the node level, the *degree centrality* measures a node's "popularity" by counting its edges. *Betweenness centrality* reflects a node's role as a "mediator" by locating the shortest paths between other nodes. *Closeness centrality* captures a node's "accessibility" as the average distance to other nodes. *Eigenvector centrality* indicates a node's ability to "transmit" network effects.

The scope of a social network can be defined either naturally by research contexts or through predefined relational criteria. According to Scott and Carrington (2011), there are typically three conventions that define the scope of a social network in empirical research, which are respectively the position-based, event-based, and relation-based approaches. While position- and event-based studies usually consider a specific context defined either by the spatial, organizational and institutional boundaries, or the scope of policy intervention and external shocks, relation-based studies consider interactions in open areas by constructing explicit selection criteria that define specific relational ties and the scope of social networks. The adoption of these conventions often depends on the objective of studies and data availability. However, spillover effects arising from relational ties that are not clearly identified usually do not fit in the scope of SNA. Take the general agricultural carbon emissions as an example, the externality stems from the aggregated individual behaviors of multiple emitters within a broad geographic region. It would lack local asymmetries that SNA employs to construct instrumental variables, seeing that individual behaviors may be influenced by the average outcome across the network, such as the average temperature shifts and precipitation changes, rather than direct peer influences.

2.2 Structural elements and information diffusion models

Diffusion models investigate how information spreads through the network (Lamberson *et al.*, 2016). The susceptible-infectious-removed (SIR) model describes the process of a "susceptible" node being "infected" after interacting with the seeding nodes before the infection gets "removed". Watts and Strogatz (1998) found that the contagion increases with clustering coefficients, and decreases with distance and degree distribution.

The threshold model further allows nodes to adapt information sets and change the infection status according to the behaviors of neighbors (Lamberson *et al.*, 2016). It shows that diffusion can be prohibited by limited initial seeding nodes and higher thresholds for behavioral changes. The model also finds that increased network connectedness has ambiguous effects, as the change of status depends on the proportion rather than number of infected neighbors.

Based on the threshold model, the herd model inspects the suboptimal diffusion in networks (Barnett-Howell and Mobarak, 2021). It considers sequential interactions within a local cluster, where agents rely on limited information sources. Simulation results find the suboptimal diffusion decreases with initial seeding nodes and average path lengths, while it increases with clustering coefficients.

2.3 Structural elements and information aggregation models

Aggregation models characterize information acquisition through social learning across the network. In Bayesian learning models, this process follows an information-updating rule based on prior beliefs and observed outcomes of neighbors. Network connectivity is therefore crucial for an effective aggregation. In the long run, the information sets will be eventually synchronized and lead to a convergence to the optimal behavior across agents.

Rather than allowing information aggregation over the entire network, the DeGroot (1974) model assumes that agents only update information sets from neighbors. It thus highlights the key role of network positions, which has been overlooked in the Bayesian model. In a fully connected network, the model predicts a convergence of information sets, with the equilibrium depending on prior beliefs, neighborhood relationships, and the relative centrality across agents.

2.4 Comparison of structural elements in aggregation and diffusion models

Table 1 shows the relative importance of structural elements in information aggregation and diffusion models. The degree distribution, clustering coefficients, density, and path length are widely considered in information diffusion models, whereas node centrality, edge weight, and tie strength are more prevalent across information aggregation models. Several network features are crucial for both types of models. For example, the average path length both affects the diffusion speed and effectiveness of information acquisition, and node centrality determines a node's accessibility in social learning and its role in strategic dissemination

Table 1. Comparison of network structural elements in information diffusion and aggregation models

Level	Category	Element	Diffusion	Aggregation
Macro	Connectivity	Average Path Length	***	**
		Degree Distribution	***	*
	Tightness	Global Clustering Coefficient	***	*
		Density	***	*
Micro	Node	Node Centrality	**	***
		Local Clustering Coefficient	***	*
	Edge	Edge Weight	*	***
		Tie Strength	*	***

Note(s): *, **, *** are indicators of the prevalence of network structures. More asterisks reflect a higher prevalence

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decisions. The next section provides a meta-analysis of the application of these elements and models in agricultural economics.

3. Integration of SNA in agricultural economics

3.1 Meta-analysis and thematic groups

To screen out thematic groups in which SNA has been applied in agricultural economics, we perform a meta-analysis of publications in field top journals in the past 2 decades. 124 papers published between 2000 and 2022 are included in the analysis. More details can be found in the supplementary material appendix.

The use of SNA in agricultural economics has been found to increase significantly over the period. Before 2012, only 2.2 papers were published each year on average, while it increased to 9.1 afterward and achieved a record-high at 15 in 2021. Journals with the most publications are the *World Development* and *Journal of Rural Studies*, each taking about 10% of the total publications (see Figure 1).

Figure 2 summarizes keywords of titles and abstracts, which demonstrates a shift of themes over time. While early studies focused on the resource allocation, knowledge exchange, and technology adoption for agents with imperfect information, recent works present more explorations of inter-organizational and international networks. Based on the keywords, we categorize the 124 articles into four thematic groups for a systematic review in the next section: (1) resource allocation, (2) knowledge and risk diffusion, (3) technology adoption, and (4) inter-organizational and international networks.

3.2 Systematic review by themes

3.2.1 Resource allocation. An efficient resource allocation hinges on the equalization of marginal outputs. Yet an essential challenge in reality is the information asymmetry between the supply and demand sides. Many studies have overlooked information spillovers through social interactions, e.g. access to credit through friends and imitation of neighbors' land-use and migration behaviors, which indicate that social networks may address the information asymmetry and produce efficient resource allocations. Compared with the assessment of spillover effects with conventional econometric models, the integration of SNA not only provides identification strategies that could provide more precise estimations, but also a means to reveal the fundamental mechanisms through which information spillovers take effect.

Using network-based models and data collection techniques, recent studies relying on SNA tools have found social networks to improve the outcomes of credit distribution by increasing both the access and repayment performance of individual farmers. Okten and Osili (2004)

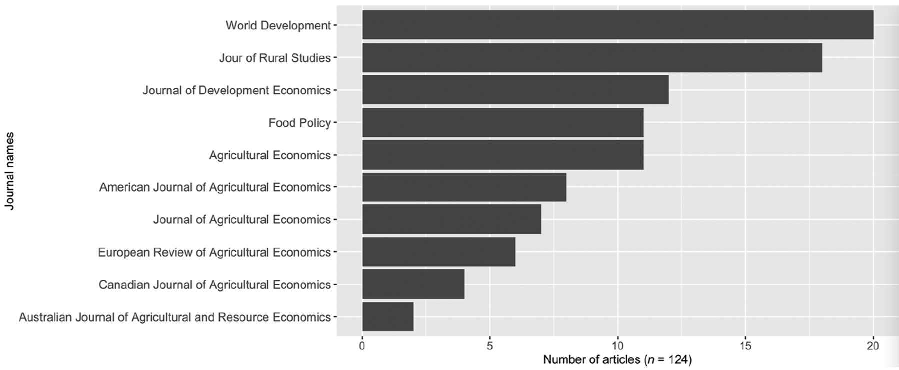

Figure 1. Number of reviewed articles by journals. **Source(s):** Created by authors

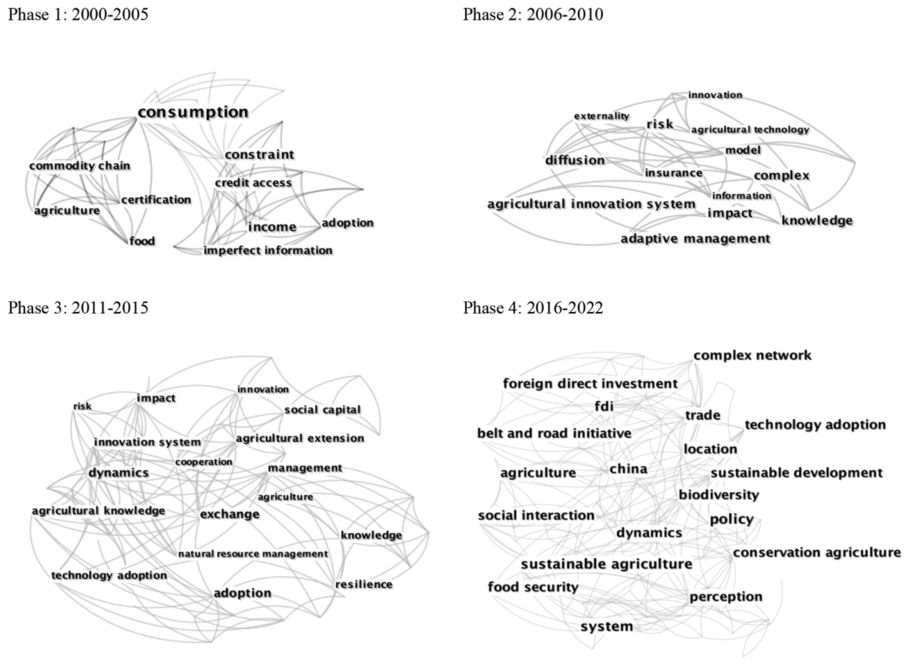

Figure 2. Major keywords of titles and abstracts of reviewed articles by period. **Source(s):** Created by authors

established a framework in which social networks can influence credit distribution through two channels. On the one hand, farmers could aggregate credit information from peers, which would lower their credit search costs. On the other hand, farmers could also transmit the private information of personal traits such as skills and trustworthiness to lenders and reduce the information asymmetry. To quantify the effect of social networks on information aggregation and variations across social ties, Dufhues *et al.* (2012) applied Name Generator (NG) and Position Generator (PG) techniques to collect network data among Vietnamese farmers. While the NG method collects direct social relations like home visitors and kins, the PG method identifies weak ties such as whether a farmer knows any teachers or doctors. Their findings demonstrated that credit access and repayment outcomes are enhanced primarily by strong social ties like family bonds. Based on an experiment of the distribution of microfinance loans among Indian farmers, Banerjee *et al.* (2013) employed the contagion and threshold diffusion models to uncover the spread process of loans and investigate how the targeting intervention in diverse farmer groups could influence the distribution outcome. They demonstrated that injecting credit resources into nodes with a high diffusion centrality could significantly enhance the overall effectiveness of microfinance loans.

In terms of land allocations, the recent literature has confirmed that an individual's position in social networks can influence both information distribution and aggregation pathways and is hence essential to the efficiency of eventual allocation outcomes. Isaac and Matous (2017) have proposed an information aggregation framework to assess how the land-use decision of individual farmers is affected by that of peers. They found that the ability of a farmer to gather information within the social network depends on the degree of centrality. Farmers with a higher degree of centrality tended to have a lower likelihood of land abandonment and cultivate more diverse cash crops. Xia *et al.* (2020) analyzed the social network across 177 Chinese farmers, finding that the land-use choice of the central farmer would influence network neighbors. They adopted a network autocorrelation model to distinguish the peer effects of various social ties, which demonstrated that the neighborhood network exhibited a stronger peer effect than the kinship network. Furthermore, the information aggregation process may generate conflicting information, which would lead to negative impacts on the land allocation outcomes. Ding *et al.* (2021) have investigated the grassland herding choice of Chinese farmers in response to ecological conservation policies. By analyzing the information source and content of grazing in the social network, they have noted that while the social learning of ecological policies and stall-feeding skills could reduce herders to grazing excessively, the conflicting information about the over-grazing experience of others would produce a counter effect.

In terms of labor migrations, the use of SNA has delineated "destination-following" patterns at regional and sectoral levels. Grounded in the "weak tie theory" of Granovetter (1973), Liu (2013) and Giulietti *et al.* (2018) have employed an NG method to compare the impacts of strong and weak network ties on the migration decision. While Liu (2013) pointed out that weak ties such as friends and acquaintances could significantly promote migration among African migrants to Europe, Giulietti *et al.* (2018) showed that strong ties like family members were the main driver of rural-urban migrations in China. With the approach of Bramoullé *et al.* (2009), Johny *et al.* (2017) integrated a social network matrix into a spatially autocorrelated model to address the endogenous network effects using behaviors of network neighbors as the instrumental variable. Their results showed an elasticity of 0.7 in network effects. Wang *et al.* (2021) have further embedded micro network structures to an agent-based model to address endogeneity between migration decisions and network connections. They found that while off-farm jobs would reduce a farmer's centrality in the social network as suggested by Baird and Gray (2014), the degree and betweenness centralities were crucial pre-determinants of decisions to leave the farm.

3.2.2 Knowledge and risk sharing. The resource allocation decision often relies on the knowledge level and risk perception of individuals. The diffusion of knowledge and management of agricultural production risks in developing nations, however, are often hindered by their underdeveloped public information services, market mechanisms, and contractual frameworks. While the role of direct interventions such as agricultural extensions in promoting farmers' knowledge and that of informal contracts in mitigating production risks have been examined, these studies have overlooked the influence of community social networks, which are critical for the dissemination of knowledge and establishment of informal contracts (Breza *et al.*, 2019).

Recent studies integrating SNA with RCTs methods reveal that knowledge interventions targeting specific individuals can produce spillover effects across the social network. Targeting well-connected individuals in the network, for example, could notably increase the speed and breadth of knowledge dissemination. However, the impact on the individual knowledge level tends to differ. Cai *et al.* (2015) conducted an RCT to explore the social network effect for the knowledge diffusion in rural China. Utilizing the NG method, researchers collected network data for the entire village. A random group of farmers were selected to learn the information of the crop weather insurance. The findings suggest that farmers in the control group would be 50% more likely to take the insurance, for each additional friend in the treatment group. Kim *et al.* (2015) carried out an RCT across 32 Honduran villages on the dissemination of health knowledge. They revealed that with targeted information to key individuals, the overall degree of knowledge diffusion was raised by 12.2%. Similarly, with a focus on the aquaculture knowledge diffusion among shrimp farmers in four Vietnamese villages, Lee *et al.* (2019) noted that while targeting central nodes in the network could facilitate knowledge spillovers, it is less effective compared with random selection strategies.

Studies integrating network formation econometric models find that the knowledge exchange among farmers is influenced both by economic characteristic similarities and network substructures. Jäckering *et al.* (2019) used a Dyadic regression to examine how socioeconomic attributes impact the agriculture-nutrition information exchange among farmers. Their estimations based on 13,318 dyads data from Kenya farmers showed that education, age, kinship and gender similarities could significantly facilitate information exchange. Additionally, Nyantakyi-Frimpong *et al.* (2019) explored how farmers share agricultural knowledge, using Exponential Random Graph (ERG) Models to assess the influence of network substructures on information flows. With a highlight of the non-closed triadic or 2-stars substructure, their findings from 104 Ghanaian farmers showed a preference for the knowledge of key individuals during social learning.

Respectively using network-based risk-sharing frameworks and network formation models, researchers have found that social networks would not only aid the enforcement of risk-sharing contracts, but also the formation of risk-sharing connections. Bloch *et al.* (2008) developed a model with negative reputation effects across the network following a deviation from the risk-sharing agreements. They found the global clustering coefficients, network density, and centrality to significantly influence the speed and coverage of reputation transmissions, and determine the stability of risk-sharing arrangements. Fafchamps and Gubert (2007) examined the influence of tie strengths on the formation of risk-sharing agreements, by analyzing 10,592 farmer pairs in rural Philippines with a dyadic regression model. They found that risk-sharing relationships were determined by both geographical proximity and kinships, alongside the age and wealth of individuals. Employing a similar strategy, Attanasio *et al.* (2012) estimated the effect of social ties on the formation of risk-sharing relationships across 70 communities of Colombia. They found that farmers already with friendship or kinship ties were three times more likely to form risk-sharing relationships, and the probability would increase by an additional 10% among farmers sharing similar risk attitudes.

3.2.3 Technology adoption. The efficiency of resource allocation is also influenced by technological constraints that individuals face. Lacks of extension services, training and infrastructure have restricted farmers' access to information and the use of advanced technologies. Traditional adoption models primarily focus on the representative agent's decision-making based on cost-benefit considerations, often assuming homogeneity in learning and diffusion processes. In contrast, the application of SNA in adoption studies refines the understanding of how farmers process and integrate peer information by incorporating individual heterogeneity and behavior interdependence, enhances policy interventions by identifying key actors for targeted dissemination strategies, and improves the predictive accuracy of diffusion models by accounting for different network mechanisms.

Recent studies have integrated information aggregation models to investigate how the technology adoption decision is affected by peer behaviors through social learning. Conley and Udry (2010) proposed a Bayesian learning model to characterize the information aggregation of input decisions. Based on the network data collected from Ghana, they revealed that input decisions depend on the payoffs of each farmer's network peers. Empirical studies also found an inverse U-shaped relationship between the adoption decision and adoption rates of peers (Bandiera and Rasul, 2006). In particular, they found a threshold of the network size, beyond which farmers might take strategic delays for further declines in the learning cost. This creates a negative externality within information aggregation through the network. With a focus on the adoption of genetic modification technologies, Maertens (2017) defined learning and non-learning networks according to whether individuals are aware of input and output decisions as well as profit outcomes of their peers. It has been identified that additional adopters could reduce the adoption rate by 4.5% in learning networks, which provides evidence of the presence of strategic delays.

Studies that integrate information diffusion models with RCTs find the technology adoption to depend on network structures. Extension services targeted at central farmers can enhance the technology diffusion. Beaman *et al.* (2021) showed a threshold model in which the centrality of initially selected trainees and the overall network connectivity determines the final coverage of technologies. With data from 200 Malawian villages, they found that selecting injection nodes using threshold models could increase village-wide technology adoption rates by 3% compared with extension agencies. Beaman and Dillon (2018) found that although targeting central nodes can facilitate the diffusion of composting techniques, females and less-connected farmers would more likely become excluded compared with random intervention strategies.

Combined with computational simulation techniques, recent studies have further used information diffusion models to predict technology diffusion outcomes in various scenarios. Extending the diffusion model of Banerjee *et al.* (2013), for example, Xiong *et al.* (2018) established a two-layer network threshold model to discern the positive effects of social learning and negative effects of environment externalities on the spread of a new crop in rural China. The simulation results revealed that the adoption was initially driven by social learning, but would instead be driven by the motivation to mitigate externalities in later stages. With a focus on climate-adaptive technologies in Ethiopia, simulation results of Bazzana *et al.* (2022) showed that denser networks can facilitate social learning and increase adoption, hence enhancing the food security and risk resilience of farmers.

3.2.4 Organization and international trade networks. Similar to that of individuals, the efficiency of resource allocation by organizations and countries across markets, stakeholders and over time is also constrained by asymmetric information. Strategic decisions of market entry, investment and innovation, therefore, are typically subject to the influence of inter-organizational and international networks. By taking these entities as independent representative agents, the existing literature has primarily overlooked how information exchange through aggregation and diffusion can address misallocations caused by imperfect contracts, incomplete policies, and external market uncertainties. However, with the integration of SNA, recent studies showed that organizations may exchange innovations with network peers to foster growth synergy, aggregate information to make entry decisions, and work with diverse organizations to facilitate policy implementation and prepare for transmitted risks from peers.

Based on information diffusion models, empirical studies have also identified the effect of synthesized innovation within organizational networks and the role of micro-level network structures. For example, Fafchamps and Söderbom (2014) introduced an innovation diffusion model to the study of investment decisions by African firms. This model posits that the information about innovations was disseminated through network peers, which created a positive externality. Organizations might also build mutual trust by information transmission, which enhances contractual relations, reduces transaction costs, and increases potential customers. Researchers have developed different types of organizational networks based on customer, supplier, and investment data to investigate the influence of network structure on firm innovation and growth. According to the field study of Ethiopian shoe-making firms, Gebreeyesus and Mohnen (2013) found a 39% increase in the probability of taking high-level innovation activities with a doubling of the firm's centrality. Greenberg *et al.* (2018) further revealed that firms with a greater degree centrality would exhibit a faster employment growth. Instead of interpersonal networks, Tuitjer and Küpper (2022) created a social network framework in which the innovation and growth performance depends on both horizontal and vertical production linkages.

With information aggregation models and network econometrics, the cross-market network effect on investment decisions has been investigated by recent studies. Patnam and Sarkar (2011) considered a situation in which firms obtain investment information from other industries. They showed that an increase of the average market investment level in other industries by one standard deviation will lead to a 0.16 standard deviation growth in the firm's investment. Firms also aggregate information across the market to make entry decisions. Chaney (2014) developed a network model which assumes that firms learn from incumbent peers to reduce search costs before entering an international market. Built upon this framework, Fertő *et al.* (2021) examined whether central firms in the trade network are more likely to enter new markets. They found that an increase of the degree centrality by one standard deviation leads to a 19% higher likelihood of forming new trade links.

Finally, the effect of inter-organizational and international networks on both policy implementation and risk contagion has been identified thanks to the integration between network diffusion models and network econometrics. Saint Ville *et al.* (2017) proposed that in the inter-organizational network, central enterprises, cooperatives, NGOs and governments played a pivotal role in implementing food security policies. Manolache *et al.* (2020) established an ERG model to investigate how organizations exchange the information about the Common Agricultural Policy across regions. They found that the 2-stars substructure played a vital role. Gephart *et al.* (2016) developed a shock propagation model to quantify the redistribution of global seafood trade flows in supply shocks. They found that regions with a high import dependency are more vulnerable to the shock transmission. Building upon this model, Gutiérrez-Moya *et al.* (2021) further demonstrated that developing countries with fewer export partners are prone to larger trade shocks.

3.3 Summary of SNA applications across themes

Table 2 reveals whether and to what extent that each network structural element is used in different topics, as a comparison of the SNA application across thematic groups. We show that the average path length, measuring the network connectivity, has been widely used to characterize the speed and scope of risk-sharing and technology diffusion in the social network of farmers. However, in inter-organizational and international networks, the degree distribution serves as an alternative indicator of the network connectivity, as it highlights the efficiency of information transmission from a random agent with many potential partners. Network tightness measures, such as the global clustering coefficient and network density, have been mostly used to study resource allocation and technology adoption to measure the allocation and diffusion efficiency.

By contrast, with regard to the micro network structural elements, centrality indices have been of a key importance in all thematic groups regarding social networks of either farmers or organizations and countries. The coefficient of local clustering is also a node-level structure frequently considered in inter-organizational and international networks. Regarding edge-level attributes, the weight and tie strength are prevalent in all types of networks and themes. In general, micro structures have been examined more intensively compared to macro ones in the literature, which confirms that SNA provides a particular tool to understand individual heterogeneities in peer network effects.

In addition, regarding the scope of social networks, we also find that the definition and structure of networks often reflect the broader socioeconomic context in which they exist. In collectivist societies, networks tend to be dense and embedded in kinships and local

Table 2. Comparison of network structural elements across thematic groups

Category	Element	Resource allocation	Knowledge/ risk sharing	Technology adoption	Org/country networks
Connectivity	Average Path Length	/	**	*	***
	Degree Distribution	/	/	/	**
Tightness	Global Clustering Coefficient	*	/	/	*
	Density	*	/	*	/
Node	Node Centrality	***	***	***	***
	Local Clustering Coefficient	/	*	/	**
Edge	Edge Weight	*	***	*	*
	Tie Strength	***	***	**	*

Note(s): *, ** and *** are indicators of the prevalence of network structures. More asterisks reflect a higher prevalence

Source(s): Created by authors

institutions, while in more individualistic societies, they often rely on professional affiliations, digital connections, and market transactions. Despite such differences, SNA provides a unified framework to analyze interactions across diverse environments.

4. Discussions

4.1 Progress of integrating SNA in agricultural economics

With a focus on changes in information sets through two mechanisms, i.e. information aggregation and diffusion, SNA provides an essential framework and toolbox to analyze the interdependent decision-making in agricultural economics. It directly characterizes behavioral interactions, by taking into account the rule of information update associated with network structures. Compared with conventional neoclassical economics in which agents are treated as independent from each other, the employment of SNA provides a renovative perspective to uncover fundamental mechanisms that give rise to peer effects. It also delivers a comprehensive empirical strategy to precisely investigate these effects, which accounts for heterogeneities and dynamics in complex, proximate and segregated real-world networks. SNA has been widely used through the entire process of empirical studies which include data collection, variable selection, and identification strategy. We identify three key contributions that the integration of SNA has provided to agricultural economic studies.

First of all, SNA has provided a theoretical lens to comprehend the interdependence in agricultural decision-making. While it has been noted for a long time that agricultural production and food consumption decisions in reality are not derived from independent individual optimization, the investigation of peer effects has primarily taken the process of interpersonal interactions as a black box such that the estimation is built on the strict assumption that such effects remain identical among individuals in the reference group. With the integration of SNA, a micro foundation based on the information set changes has been provided to systematically account for individual heterogeneities within social networks. On the one hand, information diffusion models such as simple contagion and threshold models have been constructed to identify opinion leaders and characterize the pathway of information flows. It has enabled policymakers to design effective strategies to seed the information and enhance the spread of intervention policies and coverage of impacts (Beaman *et al.*, 2021). For information aggregation models like Bayesian and DeGroot models, on the other hand, the progress has been primarily noted in the characterization of updating behaviors of less-informed agents. It enables policymakers to reduce the social learning cost by leveraging network structures (Conley and Udry, 2010).

Secondly, SNA has equipped agricultural economists with valuable alternatives for network data collection and a more complete depiction of network structures. Empirical studies of network effects depend on a reliable dataset. However, conventional data collection based on field surveys may misrepresent complicated patterns of real social networks. For example, the use of the number of friends to proxy social connections will overlook indirect connections through friends of friends and not accurately quantify the intensity of friendships. With the incorporation of NG and PG methods, SNA could describe the entire social network for a limited census survey (Breza *et al.*, 2019). With public information about organizations, a multilayered network of organizations and individuals can be further established with the use of SNA.

Finally, SNA has enhanced the precision of empirical methods in identifying social network effects within agricultural economics. The prominent challenge in identifying peer effects using conventional econometric models is the reflection problem (Manski, 1993). Particularly, the distinction between endogenous effects capturing peer influence, contextual effects of peer characteristics, and correlated effects due to peer endogenous selections requires a delicate estimation strategy in order to remove confounding factors. The integration with SNA has enabled the development of social interaction models to identify peer effects, using the average performance of distantly connected peers as the instrumental variable to reduce biases from correlated peer selections (Bramoullé *et al.*, 2009). Researchers have also integrated SNA with RCTs to identify the causality between network structures and behaviors, and assess information spillovers (Cai *et al.*, 2015). The incorporation of random formation models such as Dyadic and ERG has further enabled scholars to identify key factors influencing peer interactions at substructural levels (Jäckering *et al.*, 2019). With this more precise estimation of network effects, a more efficient and meaningful predictive network analysis could also become possible in different scenarios (Bazzana *et al.*, 2022).

4.2 Limitations and future directions of the current integration

4.2.1 Theoretical framework. While SNA has established theoretical fundamentals to model information aggregation and diffusion, existing models still face critical challenges in explaining information transmission and network structural dynamics. First of all, current information diffusion models have primarily relied on the assumption of perfect information exchange among economic agents, which has overlooked the impact of information noises on the quality of aggregation and diffusion outcomes (Banerjee *et al.*, 2013). For the technology adoption decision, for instance, misleading and inaccurate information about payoffs to peers will lead to behavioral distortions. Future studies shall thus consider information noises by explicitly modeling the probability of accurate information transmission with threshold models. They shall also characterize situations where people strategically disseminate misleading information (Bloch *et al.*, 2018).

Secondly, more psychological differences across individuals need to be considered in information aggregation models to account for heterogeneous social learning patterns. For example, empirical findings reveal that farmers tend to be inward-looking and learn from people similar to themselves, also known as “homophily” (Jackson, 2014). Other psychological factors, such as the risk preference and social pressure sensitivities, are also found to affect social learning behaviors (Maertens, 2017). Therefore, future studies shall incorporate more dimensions of node heterogeneities in behavioral motives with a focus on homophily as the priority.

Finally, while most current models have considered the influence of predetermined network structures that are taken as static on individual decisions, empirical studies find that individual decisions also depend on dynamic feedback from the network. Consider the adoption of an agricultural technology for example. Conventional mean-field game models assume that the individual decision is made according to the average adoption behaviors of other agents only. In reality, however, agents can also respond to real-time feedbacks such as the behavior of neighboring farmers, market conditions, and weather patterns. Meanwhile, the dynamics of strategic interactions among individuals may also lead to the formation of new connections and thus an evolution of the network structure. For example, the diffusion of formal credit may displace informal network connections between farmers (Banerjee *et al.*, 2021). Labor movements can change the existing network structure as well (Wang *et al.*, 2021). Hence, developing dynamic mean-field game models is critical to fully consider both dynamic network feedbacks and evolving network structures.

4.2.2 Data collection. While SNA has overcome many limitations of the conventional network data collection method through surveys, challenges remain in terms of both sample selection and social connection elicitation techniques. First, due to the limitation of funds and time, current studies mostly use social network subsamples from either random or snowball sampling. However, the failure to capture missing connections can result in measurement errors of network structures and bias estimation results. Fortunately, the development of aggregated relational data has provided an alternative to deduce the complete picture of social networks from a single subsample. In particular, the method would ask each respondent to report the number of known contacts with certain characteristics and infer network structures using network formation models. It reduces the data collection cost by 70–80% compared to the censusing approach (Breza *et al.*, 2020).

Secondly, it also remains difficult in practice to accurately elicit social connections during field surveys. For example, the setup of threshold values to the maximal number of names that can be listed is of vital importance to the appropriate application of NG and PG methods (Breza *et al.*, 2019). Aside from field surveys, future studies might benefit from the availability of big data and modern techniques to elicit social connections more accurately. For example, multimedia contents such as digital photos can be combined with field surveys to assist respondents to recall connections. Scholars can also leverage social media, mobile signals, and the Geographic Information System (GIS) data to characterize spatial and temporal dynamics of interpersonal interactions. In fact, recent works have already used geocoded mobile data to delineate the communication networks, and relied on the social media data of Facebook and Twitter to describe the friendship networks (Barnett-Howell and Mobarak, 2021).

4.2.3 Empirical estimation. While SNA has renovated the empirical approach to identify social network effects, the current strategies still face endogeneity challenges from self-selection, reverse causality, and omitted variables. Firstly, the sample selection bias in SNA could arise when similar decisions of farmers are driven by unobservable individual characters or shared external shocks. The current literature has mostly used average behaviors of distantly connected peers as instrumental variables to mitigate the bias (Johny *et al.*, 2017). However, this approach could fail if the network matrix is symmetric. To address this problem, natural experiments with randomly selected “quasi-peers” and panel fixed-effect models would provide potential alternatives to identify network effects (Bramoullé *et al.*, 2020).

Secondly, the current identification strategy with SNA also faces a serious reverse causality concern due to the interdependence between individual decisions and network connections. Most current studies have overlooked the network structure dynamics which could bias the evaluation of network intervention policies (Banerjee *et al.*, 2021). Laboratory experiments featuring exogenous network structures and random network participants, for example, can be combined with field studies to prevent reverse causalities effectively (Choi *et al.*, 2011). Meanwhile, the reverse causality problem can also be alleviated with the employment of strategic network formation models, in which the formation of network linkages and hence responses to the decision of network peers have been explicitly considered (de Paula, 2020). Using the random utility framework, for example, social connections can be modeled according to people’s similarities in socioeconomic characteristics, thus providing a way to distinguish network connections formed by individual decisions and those as exogenous conditions that shape individual decisions.

Finally, the empirical approach of SNA is also confronted with the issue of omitted variables, especially regarding multilayered networks. Individual decision-making not only depends on interpersonal interactions, but also connections to organizations, firms and other entities. Overlooking this complication of multilayered interactions can lead to an overestimated importance of peers, if all estimated spillover effects are assigned to individual networks effects. To effectively take multilayered network structures into account, future studies shall establish vertical linkages of individuals with organizations, and those of organizations with other countries, using systematic community-wide data collection schemes that cover multiple entities and a combined dataset collected from different sources (Wang *et al.*, 2013). In addition, the multilayered network structures also provide effective instrumental variables using network structures at higher-levels, such that peer effects in lower-level networks can be identified more precisely.

5. Conclusions

The integration of SNA in agricultural economics characterizes the individual decision-making by highlighting information aggregation and diffusion that yield interdependent information sets. The rapid development of virtual networks in the digital era has made information interactions more complicated, especially for the agricultural sector. This review examines key network structures, and patterns, achievements and limitations of how SNA is integrated with the conventional empirical approach of agricultural economics. We find that the SNA has been widely applied to major themes including resource allocation, knowledge and risk sharing, technology adoption, and organization and international trade over the past 2 decades. This has improved data collection methods, empirical design, and identification strategies, which has improved the estimation and understanding of network effects.

Given its interdisciplinary nature, SNA will better model interactions in individual decision-making in agricultural economics, especially in dynamic and context-specific situations, by integrating methods from other areas. For example, dynamic interactions can be simulated with complex computer science models that directly take into account intertemporal feedback. Machine learning methods could also be combined to identify key nodes of dynamic network structures (Clipman *et al.*, 2022). The further integration of psychology and sociology insights may enrich the comprehension of network effects. For example, by revealing the influence of social norms and cultural values, the utility variation with personal experience and cognitive dissonance can be delineated to model heterogeneous network effects. Incorporating these methods may also enhance the forecast of network evolutions.

Supplementary material

The supplementary material for this article can be found online.

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