EDITORIAL: SOCIAL NETWORK ANALYSIS IN MARKETING: A STEP-BY-STEP GUIDE FOR RESEARCHERS

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ABSTRACT

In a business-to-business setting, social networks comprise direct and indirect connections between firms that provide access to new information, knowledge, and resources that otherwise may not be available to the firms. Social network analysis (SNA), which refers to studying and mapping social structures through graph theory, has been widely used in many social science fields, including management. The interest in SNA is also growing among marketing scholars. This editorial discusses the main aspects of SNA and provides a step-by-step guide to researchers on how to conduct SNA in marketing, with a particular focus on the interorganizational context. The purpose of this editorial is to encourage social network research within marketing. We introduce key theoretical constructs in SNA, discuss their operationalization, and offer detailed instructions on constructing them using UCINET 6 (a common software package to implement SNA). The practical application of SNA is made on strategic alliance data collected from the Securities Data Company (SDC) Platinum database.

Keywords: *social networks, social network analysis (SNA), step-by-step guide, UCINET 6*

1. Introduction

Social networks in businesses comprise direct and indirect connections between firms that provide access to new information, knowledge, and resources. In business-to-business (B2B) marketing research, social network analysis is often used to study interorganizational relationships. Examples of such relationships typically include buyer-supplier interactions (e.g., Dekker, Donada, Mothe, & Nogatchewsky, 2019; Ekici, 2013), strategic marketing alliances (e.g., Chakravarty, Zhou, & Sharma, 2020; Swaminathan & Moorman, 2009), or board interlocks (e.g., Srinivasan, Wuyts, & Mallapragada, 2018; Wuyts & Dutta, 2008). Social network analysis (SNA) helps explore the pattern or structure of connections among firms, such as their centrality in the network (Swaminathan & Moorman, 2009) or the density of connections between their partners (Thomaz & Swaminathan, 2015), that has a significant bearing on firm strategic decisions and outcomes. In particular, B2B scholars have utilized SNA to explore how interorganizational connections affect information exchange, collaboration, and competition among firms (e.g., Schilling & Phelps, 2007; Shipilov & Gawer, 2020; Zaheer, Gozubuyuk, & Milanov, 2010).

Over time, the interest in SNA within marketing, especially in the B2B context, has grown. Grewal and Sridhar (2021) have emphasized the importance of relying on SNA to explain social network structures and dynamics, specifically in B2B markets. The main appeal of social network analysis in marketing research is that SNA allows researchers to account for the relationships among firms and the patterns and implications of these relationships. As dominant marketing thinking primarily deals with finding sources of firms' competitive advantage (Anderson, 1982; Day, 2011), SNA is becoming particularly important for marketing researchers. As almost all the firms operate within an ecosystem of their peers and often interact, compete, and collaborate with them, studying firms as separate individual entities will provide an incomplete perspective

(Shipilov & Gawer, 2020). SNA fills this void by allowing the researchers to model the complexity and dynamism of these interactions leading to novel and managerially relevant insights. For example, Chakravarty et al. (2020), Swaminathan and Moorman (2009), and Thomaz and Swaminathan (2015) utilized SNA to examine the role of interorganizational networks in explaining firm financial performance in marketing alliances. Fang, Lee, Palmatier, and Han (2016) relied on SNA to study how a firm's position in an alliance network represents a double-edged sword when launching new products: it improves incremental new product launches but harms breakthrough new product launches. In their recent editorial in the Journal of Marketing, Deighton, Mela, and Moorman (2021) urge scholars and practitioners to use the social network perspective as one of the new lenses to view marketing problems.

In Industrial Marketing Management, there has also been a growing interest in applying SNA. B2B scholars utilized SNA when studying diverse topics and applying multiple methods, ranging from case studies (e.g., Sepulveda & Gabrielsson, 2013) to quantitative methods, including complex models (e.g., small-world graphs) (e.g., Choi, Kim, & Lee, 2010). Figure 1 shows the increasing number of empirical studies utilizing SNA over time as B2B scholars are becoming more familiar with the methodology and more interorganizational network data becomes available. For example, Yaqub, Srećković, Cliquet, Hendrikse, and Windsperger (2020) have edited a special issue on "Network innovation versus innovation through networks," which includes studies looking at interorganizational networks in their various forms (strategic alliances, franchising, cooperatives, retail, and service chains) and their impact on innovation. A separate stream of research has looked at a specific type of social network called guanxi that exists in China (e.g., Badi, Wang, & Pryke, 2017; Berger, Herstein, Silbiger, & Barnes, 2015; Wang, 2007) and Et-Moone in Saudi Arabia (e.g., Abosag & Naudé, 2014). Other studies have examined the role of social networks in a firm's international activities (e.g., Fletcher, 2008;

Sepulveda & Gabrielsson, 2013) or small and medium enterprise performance (e.g., Naudé, Zaefarian, Tavani, Neghabi, & Zaefarian, 2014).

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Informed by the growing recognition of SNA research in B2B marketing, this editorial aims to promote SNA in B2B marketing and encourage B2B scholars to leverage the methodology to draw unique and novel insights. The editorial attempts to be a systematic guide about the key constructs in SNA and to provide the B2B reader B2B a step-by-step manual to apply SNA to research problems. In the editorial, we discuss commonly used social network variables at two levels of analysis: *actor-level (i.e., firm- or individual-level)* and *network community-level* (Sytch & Tatarynowicz, 2014). At the actor level, we distinguish between the *ego-network perspective* and the *whole-network perspective* that B2B scholars have often relied on (e.g., Chakravarty et al., 2020; Srinivasan et al., 2018). While the ego-network perspective considers only a firm's direct connections with its partners and connections between these direct partners, the whole-network perspective also considers all possible connections of a firm's partners and connections of these partners' partners (Borgatti, Everett, & Johnson, 2018). We further discuss the small-world properties of a network (Watts & Strogatz, 1998) and *the network community perspective*.[1] It is worth acknowledging that the network community-level has not received much attention in B2B marketing, even though firm outcomes have been shown to vary with the characteristics of network communities (Sytch & Tatarynowicz, 2014). Relying on strategic alliance data collected from the SDC Platinum database (the most frequently used database to analyze alliance networks) (e.g., Gulati, Sytch, & Tatarynowicz, 2012; Lavie, Lunnan, & Truong, 2022; Schilling,

[1] Please see Section 2 for the detailed discussion of social network variables.

2009), we provide a step-by-step guide for constructing an interorganizational network and deriving social network variables.

2. Overview of social network concepts, measures, and studies

This section starts by providing an overview of different perspectives to investigate the effect of social networks on firm or other actor behavior and outcomes and defines key terminology used in SNA. We then describe the social network concepts and the correspondent measures that have been widely utilized in marketing and management research. We review selected papers on each concept and elaborate on the mechanisms and the measures used by the authors. The section demonstrates the importance of these concepts in building knowledge on various marketing and management topics and highlights their role in generating new insights for academic literature.

2.1. Social network perspectives

Prior research has acknowledged the multi-layered nature of a firm's embeddedness in social networks. Firms' or other actors' position in the social network has traditionally been studied by B2B scholars from the ego network or the whole network perspective (e.g., Chakravarty et al., 2020; Swaminathan & Moorman, 2009). The *ego network* perspective posits that firm behavior and performance are shaped by the firm's immediate surroundings comprising direct connections to its partners and the partners' connections among themselves (e.g., Ahuja, 2000; Frankenberger, Weiblen, & Gassmann, 2013; Kumar & Zaheer, 2019). A firm's ego network is a part of the *whole network (i.e., the entire network)*—a broader social space (often limited to an industry) that includes firms' overall structure and connections. Where a firm is located in the whole network, such as the network's core (i.e., center) or its periphery, matters for this firm's access to information and knowledge flows (e.g., Hernandez & Shaver, 2019; Rosenkopf & Schilling, 2007; Swaminathan & Moorman, 2009). In-between ego and whole networks are *network communities*, which are defined as dense, non-overlapping structural groups within the entire network (Fortunato, 2010) containing pockets of homogeneous knowledge (Sytch & Tatarynowicz, 2014). These three layers are depicted in Figure 2.

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2.2. Key terms in SNA

It is important to mention that studies utilizing SNA often use specific terminology. An ego network involves a particular node, called an *ego*. A *node* or an *actor* is an entity (e.g., a firm or an individual) making up the network. The nodes to which the ego is connected are called *alters*, and the connections between nodes (e.g., alliances and board interlocks) are called *edges*. When an edge joins two nodes, they are said to have a *tie* (Borgatti et al., 2018). A tie is considered undirected when the relationship is mutual and reciprocal, as in strategic alliances and many other B2B arrangements (Kim, Howard, Cox Pahnke, & Boeker, 2016).

On the other hand, a *directed* tie implies that there is no reciprocity in the relationship, with information flowing one way. Much social network research in marketing and management assumes that the ties are *undirected* (e.g., Chakravarty et al., 2020; Swaminathan & Moorman, 2009; Sytch, Tatarynowicz, & Gulati, 2012). However, some recent studies have called to account for potential directionality in the relationships (e.g., Tóth, Naudé, Henneberg, & Ruiz, 2021; Tóth, Peters, Pressey, & Johnston, 2018). The network in Figure 2 is undirected, as can be understood from the absence of directionality in the lines connecting two nodes. The directionality can be denoted using arrows showing the direction of information flow.

One way to represent a matrix is through a graph, as in Figure 2. Another way to (mathematically) conceptualize a network is through the *adjacency matrix*—a matrix in which the columns and rows denote nodes and entries in row i and column j denote ties from i to j. For undirected networks, the adjacency matrix is *symmetric*, i.e., the top right half of the matrix (above the main diagonal) will mirror its bottom half. In Figure 3, we depict a simple undirected network and its respective adjacency matrix.

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2.3. Actor-level measures: an ego network perspective

The following section discusses three key measures used in SNA from an ego network perspective: ego network size (degree centrality), network constraint, and ego network density.

2.3.1. Ego network size (degree centrality)

The most obvious and straightforward measure we can apply to an ego network is the total number of an ego's direct ties to alters, also known as *ego network size* or *degree centrality*. Unlike other centrality measures, degree centrality is calculated without requiring information about the whole network in which a particular ego is embedded. Degree centrality could be considered a measure of prominence but, unlike other centrality measures, it does not necessarily indicate the importance of a node in connecting others (Borgatti et al., 2018; Wasserman & Faust, 1994). In an undirected network, degree centrality is calculated as a row (or column) sum of the adjacency matrix X. Formally, degree centrality of actor i, d_i, is expressed as:

(1) $d_i = \sum_j x_{ij}$, where x_{ij} is the (i, j) entry of the adjacency matrix.

Degree centrality has been utilized in much earlier and current work. For instance, Powell, Koput, and Smith-Doerr (1996) demonstrate that a firm's centrality in the network of R&D alliances helps it enhance organizational learning, creating wider collaboration opportunities by becoming an attractive alliance partner in the future. In interesting research analyzing firm behavior, Ranganathan and Rosenkopf (2014) explore how firms' degree centrality influences their voting behavior in a technological standards-setting committee. They show that firms with higher degree centrality in the knowledge network exhibit a lower disposition toward adopting standards that will make knowledge sharing easier. In a recent paper, Chakravarty et al. (2020) use the context of new product alliances to study how asymmetry in degree centrality between a firm and its partner affects a firm financial performance. The results imply that while a moderate asymmetry in degree centrality benefits the focal firm, a high asymmetry creates a power imbalance causing mistrust between partners, ultimately lowering financial returns from alliances. These papers show that degree centrality is a simple yet powerful concept that can be applied to explore different facets of a firm's behavior and outcomes.

2.3.2. Network constraint

Perhaps one of the most common measures to calculate in ego networks is Burt's (1992) *network constraint.* Network constraint captures how ego is connected in alters who invest their time and energy in each other. Time investment of actor i in actor j can be measured by the proportion of i's contacts with j relative to the total number of i's contacts. Formally, Burt's network constraint of ego i is expressed as:

(2) $C_i = \sum_j c_{ij}$, where $c_{ij} = \left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2$ for $q \neq i, j$.

C_i is the aggregate constraint on i that is the sum of constraints from i's relationship with each of N contacts. p_{ij} is the proportion of i's network time and energy invested in contact j.

Network constraint normally takes values between 0 and 1 (Borgatti et al., 2018). A firm's network constraint is high when it has few contacts and those contacts are strongly connected to one another. If we take a network in Figure 3, A1 will have the lowest value of network constraint (0.544), followed by A5 (0.792), A2 and A3 (0.835 for both), and A3 (1.000).

Management and marketing scholars often use the *inverse* of network constraint to capture a firm's *brokerage advantage*, which measures "access to a wider diversity of information, early access to that information, and control over information diffusion" (Burt, 2005, p. 16). The brokerage advantage of firms has been studied from several perspectives in management research. For example, Koka and Prescott (2008) study brokerage advantage in alliance networks in the context of environmental changes in the steel industry and find that firms possessing brokerage advantage perform better. Their research highlights that brokerage advantage helps firms acquire appropriate skills and capabilities in the changing environment. In another study, Iurkov and Benito (2018) investigate how the positioning of firms in their domestic network of strategic alliances affects their geographic scope, i.e., whether they concentrate on their home region or expand beyond it. The authors find that the relationship between the brokerage and home-region orientation is nonlinear, as excessive brokerage advantage can also lock firms in their domestic environments by facilitating the development of location-bound firm-specific advantages. In the innovation literature, Wang, Rodan, Fruin, and Xu (2014) study brokerage advantage in a firm's collaborators network and knowledge network. They find that the brokerage advantage of collaborators in the network increases exploration, as a brokerage is key to searching and combining disparate knowledge elements. So overall, brokerage advantage explains the connection and information benefits a firm may enjoy in a social network but, at the same time, ties it closely to the context of the study.

It is worth acknowledging that network constraint is a function of ego network size. The logic is that an actor acquires social capital (e.g., through access to information) by connecting to each additional alter and loses capital with the extent to which the alters are connected (Burt, 1992, 2005). This may have implications for research design. For example, Borgatti et al. (2018, pp. 321-322) suggest that "researchers using [brokerage] as an independent variable in a regression should not control for degree [centrality], as degree [centrality] is one of the two factors that make up the concept."

2.3.3. Ego network density

Ego network density measures limits to an ego's behavior (e.g., potential exposure to opportunism and violation of social norms) since its alters are tightly interconnected. It captures the proportion of the ego's alters who are interconnected. More precisely, ego network density is calculated as the number of actual ties between ego's alters divided by the total number of ties possible (Borgatti et al., 2018). The resulting number is therefore bound between 0 and 1, where the latter indicates high ego network density (i.e., every possible tie is also an actual tie).

The concept has been used in marketing and management to reveal several important aspects of firm behavior. For example, Swaminathan and Moorman (2009) examined marketing alliances and found that high partners' interconnectedness improved information transfers between the network and the new alliance and reduced partner opportunism, positively affecting shareholder return from alliance formation announcements. On the contrary, Bae and Gargiulo (2004) studied alliances in the U.S. telecommunications industry and found that network density had a significant adverse effect on profitability, suggesting that the lack of connections among a firm's partners may be a significant barrier to effective cooperation. Interestingly, Thomaz and Swaminathan (2015) argue that at low levels of ego-network density, the idiosyncratic risk in marketing alliances decreases, and at high levels, idiosyncratic risk increases. When ego-network density is high, firms begin to act similarly and resemble each other, diminishing the impact of diversification and brand equity strengthening associated with the reduced idiosyncratic risk. So overall, we could conclude that high ego-network density is useful to facilitate information flows in a firm's immediate environment but can reduce a firm's exposure to new opportunities.

Importantly, scholars pointed out that the measure of ego network density is sensitive to the inclusion of ego network size (Phelps, 2010). Borgatti et al. (2018) mentioned that controlling for the latter in regressions involving ego network density is important.

2.4. Actor-level measures: a whole network perspective

Beyond their ego networks, firms and other actors can also be studied as to their position in the entire network (see the top graph in Figure 2). *Centrality* is a key property of a node's position in the network—it is broadly defined as "the importance of a node due to its structural position in the network as a whole" (Borgatti & Li, 2009, p. 15). Centrality is characterized by a family of concepts. The most commonly used by marketing and management scholars are degree, eigenvector, betweenness, and closeness centrality. We have noted that degree centrality is calculated without requiring information about the whole network in which a firm is embedded, which is not the case for other centrality measures.

2.4.1. Eigenvector centrality

Eigenvector centrality is a widely used measure in marketing and management research (Shipilov & Gawer, 2020; Zaheer et al., 2010). It is a function of the centralities of an actor's connections: high eigenvector centrality implies that a firm has many connections to partners that have many connections to their partners (Bonacich, 1972, 1987, 2007). Formally, the eigenvector centrality of actor i, e_i, is expressed as:

(3) $e_i = \lambda \sum_j x_{ij} e_j$, where λ is a proportionality constant called the eigenvalue.

Marketing and management scholars often use eigenvector centrality to capture a firm's status and power in the network (Granados & Knoke, 2013; Piazza & Castellucci, 2014; Podolny, 2001). Having higher eigenvector centrality can attract more partners as firms often choose to work with other firms chosen by other well-connected firms (Ahuja, Polidoro, & Mitchell, 2009; Gulati & Gargiulo, 1999). Srinivasan et al. (2018) used this measure to assess a firm's connectivity to other well-connected firms in the board interlock network. The authors showed that firms with higher eigenvector centrality have a higher number of new product introductions due to greater access to information on the environment (i.e., market intelligence). Similarly, Sauerwald, Lin, and Peng (2016) demonstrated that the board social capital measured using eigenvector centrality was linked to higher CEO-related returns. Boards positioned at the center of the network offer access to external social capital, such as strategic opportunities. Interestingly, Koka and Prescott (2008) found an adverse effect of a firm's eigenvector centrality in an alliance network on firm performance following a radical change in the industry. Their analysis showed that alliance networks might not have the necessary information for quick and effective strategic responses in the industry.

Most social network analysis software, such as UCINET 6 (Borgatti, Everett, & Freeman, 2002), can compute eigenvector centrality, normalizing the score between 0 to 1 using different techniques. For example, because interorganizational research often involves panel data, scholars prefer normalization for the largest possible or observed value to allow better inter-year comparison (e.g., Hallen, Katila, & Rosenberger, 2014). Calculating eigenvector centrality for the actors in Figure 3 yields a higher value for A1, which A5 closely follows, and then A2 and A4.

2.4.2. Betweenness centrality

Betweenness centrality is another well-known type of centrality (Freeman, 1979) that is frequently utilized in marketing and management research (Shipilov & Gawer, 2020). It is often used to measure a firm's access to industry-level structural holes (Iurkov & Benito, 2020; Shipilov, 2009). A *structural hole* is the lack of ties between groups (called *clusters* or *communities*) of tightly interconnected actors in the network (Borgatti et al., 2018). Linking these unconnected groups offers a firm different points of view. The firm can also play the groups off against each other to its benefit (Burt, 1992, 2005).

Technically, firms have high betweenness centrality if they lie along many shortest paths between pairs of others in the whole network. The *shortest path* is the path that connects pair of nodes via the smallest number of edges (Borgatti et al., 2018). For example, in a supply chain network, a firm has high betweenness to the extent that all of the shortest chains from manufacturers to end consumers pass through that firm (Borgatti & Li, 2009). Formally, betweenness centrality of actor i, b_i, is given by:

(4) $b_i = \sum_j g_{jik}/g_{jk}$, where g_{jik} is the number of shortest paths connecting j and k through i, and g_{jk} is the total number of shortest paths connecting j and k, $i \neq j \neq k$.

Scholars often used betweenness centrality to study various innovation outcomes. Gilsing, Nooteboom, Vanhaverbeke, Duysters, and Van Den Oord (2008) found that a firm's betweenness centrality has an inverted-U relationship with the amount of its technological exploration. This can happen because firms have to deal with a higher volume of diverse information at high levels of betweenness. This consumes time and resources that cannot be allocated for absorbing and integrating novel insights. Similarly, Fang et al. (2016) showed that a firm's betweenness centrality is useful for incremental innovations but can hurt radical innovations. The construct was also used to study aspects of firm behavior. Analyzing this construct in the context of foreign divestment decisions, Iurkov and Benito (2020) revealed a positive association between an increase in firm betweenness in the domestic network and foreign divestment. Increased access to information about new business opportunities and the resulting opportunity costs of maintaining foreign operations subsequently lead to their divestment.

An actor's betweenness centrality is equal to zero when it never lies along the shortest path between any two other actors. It happens when the actor is isolated or when every alter of an actor is connected to every other alter (Borgatti et al., 2018). Social network analysis software also often produces the normalized betweenness score obtained by dividing betweenness centrality by the maximum possible value, i.e., $(n-1)(n-2)/2$, where n is the number of actors in the network. Marketing and management researchers often resort to using normalized betweenness centrality scores as they ensure across-year comparability and are not sensitive to changes in network sizes (Allatta & Singh, 2011; Hagedoorn & Duysters, 2002; Soh, Mahmood, & Mitchell, 2004). In Figure 3, the highest betweenness centrality is attributed to A1. A5's betweenness is low but not zero (0.5 versus A1's value of 3.5). A2, A3, and A4 have zero betweenness centrality.

2.4.3. Closeness centrality

Closeness centrality measures an actor's ability to reach all the other actors in the network quickly—actors that score high on closeness centrality are likely to receive information more quickly than others (Borgatti et al., 2018). Closeness centrality of actor i, $close_i$, is calculated as the reciprocal of the sum of the actor's shortest path lengths, s, to all other actors (Freeman, 1979):

(5) $close_i = \left(\sum_j s_{ij}\right)^{-1}$, where $i \neq j$.

Closeness centrality is perhaps the least used centrality metric in interorganizational research. However, it found application in B2B research, particularly on strategic alliances. In their study of the relationship between firm network connectivity and innovation, Powell et al. (1996) used closeness centrality to measure a firm's dependence on others for access to information. Powell et al. (1996) found that closeness centrality was linked to sales growth as it provided learning opportunities to a firm. Later research pointed to dark sides of closeness centrality. Fang et al. (2016) observed that having higher closeness centrality increases the number of incremental new product launches but decreases the number of breakthrough launches. The authors argued that closeness centrality could inhibit a firm's ability to explore ideas outside the industry. Similarly, Iurkov and Benito (2018) find that excessive levels of closeness centrality in the domestic network of strategic alliances may constrain a firm's propensity to venture abroad through a lock-in effect. Thus, scholars found that closeness centrality can be a double-edged sword in influencing firms' strategic decisions and outcomes.

For comparison purposes, one can normalize the closeness centrality score by dividing it by the maximum possible value, $1/(n-1)$. In networks consisting of several disconnected parts (components), distances between actors in these parts have no path between them. Some ways to deal with this could be by taking the reciprocal of each dyadic distance and giving a zero value as the proximity of two actors in different parts (Borgatti et al., 2018).

2.5. SNA at the network community-level

2.5.1. Network communities and small-world systems

The network community perspective has escaped the attention of scholars and requires further investigation. Recent research in marketing and management has pointed that social networks, such as networks of strategic alliance or board interlocks, are composed of *network communities* (also called *network clusters*)—structural groups of actors that have many ties internally and few ties externally (e.g., Gulati et al., 2012; Sytch & Tatarynowicz, 2014). Each community has its unique structure of relationships and idiosyncratic flows of information (Baum, Shipilov, & Rowley, 2003; Gulati et al., 2012; Reagans & Zuckerman, 2001), and only a few actors in the network span the boundaries of these communities. Such a structural configuration of a social network is known as a *small-world system* (Watts & Strogatz, 1998).

Knowing whether a social network is a small-world system tells about the presence of entrepreneurial opportunities for recombining diverse knowledge and resources across different communities (Gulati et al., 2012). Schilling and Phelps (2007) found that small-world properties in an industry-wide network positively influenced firms' innovation performance. Small-world systems are not static. In their analysis of the global computer industry, Gulati et al. (2012) observed certain evolutionary dynamics of the small-world system. They showed that a small-world system could be a highly dynamic structure: an increase in the small-worldliness of the system was followed by its later decline. Hence, the time to internalize the entrepreneurial opportunities in the industry network may be limited.

To understand whether a social network functions as a small-world system in a given year, scholars can calculate the *small-world quotient*, which indicates how connected and cohesive the relations in the whole network are (Watts & Strogatz, 1998). If a value of the small-world quotient exceeds 1, the network is said to have small-world properties. As noted by Uzzi and Spiro (2005, p. 455): "The more links between [network communities] increase in frequency, which potentially enables the creative material [within network communities] to be distributed throughout the [whole] network."

2.5.2. Detecting network communities

Therefore, it is crucial to understand what network communities compose a whole (entire) network (as in the top graph in Figure 2) and then study their characteristics. One widely used community detection algorithm in the interorganizational networks literature is the *Girvan-Newman algorithm*. The algorithm involves "iterative removal of edges from the network to split it into communities, the edges removed being identified using one of several possible "betweenness" measures, and second, these measures are, crucially, recalculated after each removal" (Newman & Girvan, 2004, p. 1). As a result, the algorithm produces non-overlapping communities of actors (i.e., each actor can only be a member of a single community in a given network). Characteristics of communities identified by the Girvan-Newman algorithm explain heterogeneity in firm behavior and outcomes in various interorganizational settings (Gulati et al., 2012; Sytch & Tatarynowicz, 2014; Tatarynowicz, Sytch, & Gulati, 2016).

Applying the Girvan-Newman algorithm to a small undirected network can be seen in Figure 4, an extended version of the network in Figure 3. The algorithm generated two communities (red circles and blue squares). It is important to note that the Girvan-Newman algorithm is best applied to smaller networks, such as networks of strategic alliances in a given industry. However, the computing speed of the algorithm is slow on networks with more than 1,000 nodes. Yang, Algesheimer, and Tessone (2016) indicate that the *multilevel algorithm*, which uses modularity as the convergence criterion (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008), outperforms other algorithms taking into account both *accuracy* and *computing time*.

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It is important to add that networks in interorganizational research may have more than one *component*—"a maximal set of nodes in which every node can reach every other by some path" (Borgatti et al., 2018, p. 18). For example, if we extend the network in Figure 3 to add A6 and A7 that are connected between themselves and are in no way connected to A1-A5, we will have two components. The component with the largest number of interconnected actors is called the *main component*. Some of the existing studies in interorganizational literature apply the Girvan-Newman community detection algorithm to each alliance network's main component while considering the smaller components to be stand-alone communities (e.g., Sytch & Tatarynowicz, 2014).

2.5.3. Within-community density

One of the key network community-level properties is *within-community density*, which is expressed as the extent of interconnections among actors of a specific network community (Gnyawali & Madhavan, 2001). It influences the speed of information and knowledge diffusion among community members and, as a result, the efficiency of cooperation and the presence of common norms (Gilsing et al., 2008). The construct is calculated as the actual number of ties divided by the number of all possible ties within the community (Borgatti et al., 2018). Importantly, one should distinguish between ego-network density and within-community density since the constructs are at different levels of analysis. Both constructs can interact to increase actor behavior and performance: high within-community density ensures rapid flows of information and knowledge between network community members while low ego-network density provides firms with opportunities to secure new information and diverse perspectives (Burt, 2005; Gnyawali & Madhavan, 2001).

Dense network communities also facilitate the build-up of trust and constrain opportunism, making information from any community richer and more reliable. This ultimately helps firms assess the reliability of technologically distant sources of novelty as well as understand and evaluate these sources (Gilsing et al., 2008). On the other hand, firms located in highly dense communities are less likely to gain new or additional information from their indirect ties, reducing access to new novel knowledge (Gilsing et al., 2008). Iurkov and Benito (2018) argued that excessive within-community density inhibited the development of new knowledge, decreasing their competitiveness worldwide and limiting their geographic scope domestically.

Density is not the only community characteristic that exerts an effect on firm behavior and outcomes. An interesting stream of research finds that the turnover of community members in a firm's network community has an inverted U-shaped effect on the firm's invention productivity: network communities characterized by moderate membership turnover can avoid the homogenizing tendencies without threatening the stability of these communities' collaborative routines (Sytch & Tatarynowicz, 2014). However, these additional indicators are outside this editorial's scope as we only focus on the most popular social network constructs.

3. Interorganizational datasets for SNA

There are several databases used to study interorganizational networks by marketing and management scholars. Some are generic, while some specialize in specific sectors. SDC Platinum is one of the most extensively used generic databases on interorganizational relationships. It provides access to information about a wide range of financial deals, including securities trading, venture capital investments, and mergers and acquisitions. Strategic alliance data are available within the "Joint Ventures/Alliances" section of the database. SDC collects these data from various sources, including U.S. Securities and Exchange Commission (SEC) filings, corporate news, and trade publications. It tracks various types of alliances, including joint ventures and non-equity alliances, research and development, marketing, manufacturing, licensing and distribution agreements, alliances with government or private organizations, and private or public companies (Schilling, 2009). According to SDC manuals, alliance coverage has been available since 1988 (Anand & Khanna, 2000). The key advantage of the SDC Platinum database is a user-friendly interface that allows searching and extracting information related to an alliance (e.g., announced and effective dates, function, industry, geography) and parties involved (e.g., industry, country of origin, ultimate parent, public status). One can download all selected information as an Excel spreadsheet that can then be exported to Stata or other software for further analysis. The downsides of the database are occasional errors in coding (e.g., few alliances may be reported as belonging to incorrect industry SIC codes), requiring verification of alliance information (Schilling, 2009). The database also lacks alliance dissolution data, requiring an assumption about alliance duration. However, the reason for this is unrelated to the database itself but rather to the lack of companies' reporting of alliance terminations. SDC Platinum is probably the most widely used database in management and marketing studies (e.g., Gulati et al., 2012; Hernandez & Shaver, 2019; Iurkov & Benito, 2018; Lavie et al., 2022; Lin, Yang, & Arya, 2009).

4. Implementation of social network analysis

This section demonstrates how to conduct SNA in an interorganization setting. Specifically, we have chosen to construct and analyze a network of strategic alliances in the global software industry (three-digit SIC code 737) as of 2018. Empirical evidence shows that software industry firms frequently form strategic alliances (Schilling & Phelps, 2007). Occupying more beneficial network positions in this industry allows firms to access diverse knowledge related to new technologies and trends and discover ways to increase operational efficiency and innovation performance (Schilling, 2015).

4.1. Step 1: constructing a network of strategic alliances

Prior to deriving social network measures, one needs to construct an alliance network with the specified boundaries. We follow the analytical procedures developed in prior research to construct alliance networks, which are normally bound within the context of a specific industry (e.g., Gulati et al., 2012; Rosenkopf & Schilling, 2007). Commonly, an alliance network in an industry in a given year consists of active alliances in which at least one partner is a member of this industry, and the primary alliance activity also has to fall within this industry (e.g., Gulati et al., 2012; Rosenkopf & Schilling, 2007; Sytch & Tatarynowicz, 2014). Therefore, we adopted this routine to define and construct an alliance network in the software industry in 2018.

We first extract information on firms' strategic alliances from the *SDC Platinum* database, which is widely used in interorganizational research (Schilling, 2015). Because firms (and databases in this regard) rarely report precise alliance termination dates, we follow prior research in modeling a five-year lifespan for an alliance (Lavie, 2007). In other words, our alliance network as of 2018 will consist of alliances formed between 2014 and 2018.

For the sake of simplicity, we will limit our SNA to firms located in the network's main component, which consists of 652 unique edges and 576 nodes (firms). Networks of this size are easy and convenient to analyze in *UCINET 6* (Borgatti et al., 2002)—a popular social network software package. We have used version 6.733 of the software. We discuss how to proceed with data inputting and separating the main component in UCINET 6 in the Appendix.

It is worth noting that other software packages exist, among which are *igraph* package in R (Csardi & Nepusz, 2006) and *nwcommands* package in Stata (Grund, 2014). The former can handle large interorganizational networks very well and provides functions for graph visualization, computing centrality scores, and generating random and regular graphs.

4.2. Step 2: Deriving actor-level social network measures

The way to derive actor-level social network measures in UCINET is rather straightforward. In the Appendix, we provide a set of detailed instructions on this. Tables 1 and 2 report the results. Table 1 shows actor-based social network measures for the first 20 firms (out of 576 firms constituting the main component). In Table 2, we provide some descriptive statistics (mean and standard deviation) and bivariate correlations between the measures (now for the sample of 576 firms). As can be seen from the tables, firms with high degree centrality usually score low on network constraint (or high on network brokerage) and high on eigenvector, betweenness, and closeness centrality. However, sometimes firms with relatively high degree do not always have high eigenvector, betweenness, and closeness centrality. For example, relative to other high-degree firms, Alibaba Group Holding has a similar degree centrality. Yet, it has low status in the network as shown by low eigenvector centrality, a substantial number of redundant connections as demonstrated by low betweenness centrality and high network constraint. It is likely embedded in a community located away from the rest of the network, as demonstrated by low closeness centrality.

-----INSERT TABLES 1 AND 2 ABOUT HERE-----

4.3. Step 3: Partitioning the network into network communities and calculating within-community density

Earlier, we mentioned that interorganizational networks are characterized by small-worldliness, signaling the presence of entrepreneurial opportunities in an industry (Gulati et al., 2012). It is important to understand whether an interorganizational network has a small-world property and what communities compose it. Interorganizational research often ignores the network community level of analysis with few exceptions. For example, the composition of network communities in alliance networks has been shown to influence firm outcomes, such as innovation performance and geographic scope (e.g., Iurkov & Benito, 2018; Sytch & Tatarynowicz, 2014). A detailed discussion on how to derive the small-world quotient in UCINET 6 can be found in the Appendix. However, it is important to remember that within-community density is not the only measure scholars could and should use when studying how community-specific factors influence firm behavior and performance. As mentioned earlier, Sytch and Tatarynowicz (2014) investigate how the turnover of community members in a firm's network community influence firm innovation performance. These types of measures and their effects need to be calculated using data conversion syntaxes available in such software packages as R or Stata, yet that is not within the scope of this editorial.

Overall, it should be acknowledged that UCINET is not the only software available for researchers to conduct SNA; it can also be implemented in R or Stata. There are certain advantages and disadvantages when choosing another software for SNA. UCINET was explicitly designed to conduct SNA; it is intuitive and user-friendly, suitable for specialists and those new to SNA. UCINET is perfectly suitable to analyze interorganizational networks in terms of computational complexity, as such networks are often bounded to a specific industry and are not very large. However, the disadvantage of UCINET is its lack of ability to effectively handle the analysis of big data on networks containing many connections. This can happen when one aims to shift the level of analysis to an individual, for example, to analyze the structure of network connections of CEOs, executives, and directors, including several hundred thousand individuals (e.g., El-Khatib, Fogel, & Jandik, 2015). R would be much more suitable for analyzing large social networks (e.g., using the *igraph* package), though it would require more specific knowledge on how to work with it. In turn, Stata may be more intuitive to conduct SNA with common software packages such as *nwcommands*, as most marketing and management scholars already use it as their default software for statistical analysis. However, it has the same disadvantage as UCINET as it does not efficiently handle large amounts of social network data and has limited functionality.

5. Discussion and conclusion

SNA is a powerful tool to analyze how interorganizational ties (e.g., strategic alliances and board interlocks, among others) are structured and how such structures influence firm-level strategic decisions and outcomes. This editorial has therefore aimed to discuss the main aspects of SNA and show how B2B scholars and practitioners can use it to study outcomes relevant to marketing. We describe the most common social network concepts, the theoretical mechanisms behind them, and their operationalization. Using the context of a strategic alliance network in the global software industry, we show how these key social network variables are distributed and relate to each other in this B2B setting. We provide detailed instructions on constructing a network and calculating the social network variables utilizing UCINET (Borgatti et al., 2002)—a user-friendly software widely used in management research.

The editorial has important implications for B2B marketing research. It provides a comprehensive view of SNA that can be conducted at different levels of analysis (firm or network community-level) and involve the calculation of a wide range of social network variables (e.g., Chakravarty et al., 2020; Iurkov & Benito, 2018; Rosenkopf & Padula, 2008). The editorial hopes to broaden the social network research within B2B marketing that has rarely examined the role of social network variables beyond the ego-network perspective (e.g., Chakravarty et al., 2020; Thomaz & Swaminathan, 2015). We emphasize that a wide range of other social network variables capture a firm's position in the whole network. We additionally point attention to network community structures that may be critical for B2B marketing-related outcomes yet remain largely under-researched in the marketing field. B2B scholars could further examine the role of network communities and their structure for firm new product introductions. If the social network has small-world properties (e.g., Gulati et al., 2012), a firm's participation in such a network can provide access to tacit and non-redundant knowledge that opens access to various entrepreneurial opportunities and stimulates innovation activities.

Although SNA in B2B marketing has been primarily used in the context of strategic alliances or board interlocks (e.g., Chakravarty et al., 2020; Srinivasan et al., 2018; Swaminathan & Moorman, 2009), it may be applied in a variety of other contexts to solve marketing problems. For example, one could conduct SNA of the multiplex social networks combining interorganizational ties and connections formed by cross-border sales teams of the marketing department within a firm to study how such network structures can jointly facilitate the diffusion of new knowledge and technologies within the firm. Another promising area within marketing to apply social network analysis is to study ecosystems, such as innovation or digital or technology ecosystems. It could lead to B2B researchers answering many promising questions, such as how a firm's presence in innovation or digital ecosystems influences its speed of innovation, technology adoption, or recovery from market disruptions. Finally, B2B scholars could combine SNA with other methodological approaches like surveys or interviews and conduct a multi-method study to tease out the link between social network variables and firm outcomes and the underlying mechanisms of such relationships. This would address the SNA's limitation of not being able to capture the processes like diffusion of information or social norms in the social network directly.

In sum, the editorial provides a valuable guide on how to conduct SNA in marketing that can be helpful for B2B scholars and practitioners when examining the influence of social networks on relevant firm-level outcomes.

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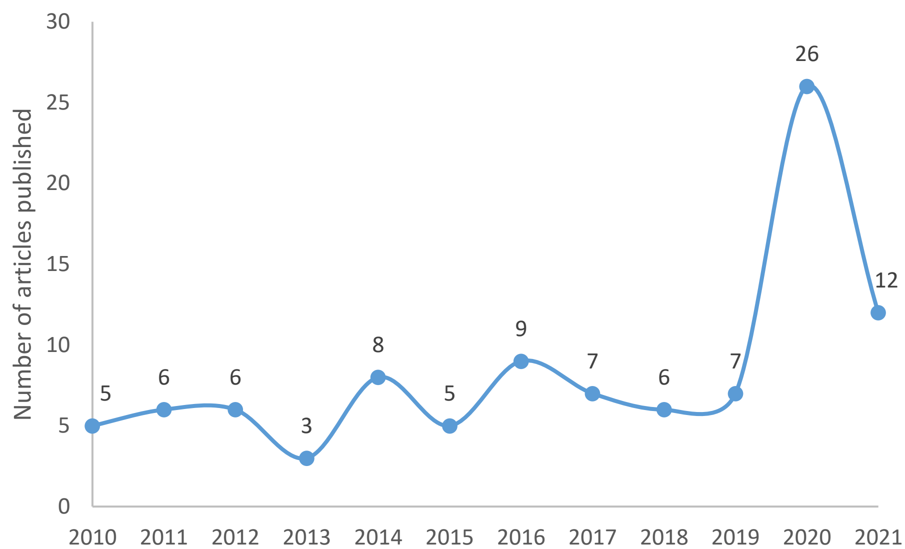

Figure 1. Empirical studies utilizing SNA in Industrial Marketing Management by year

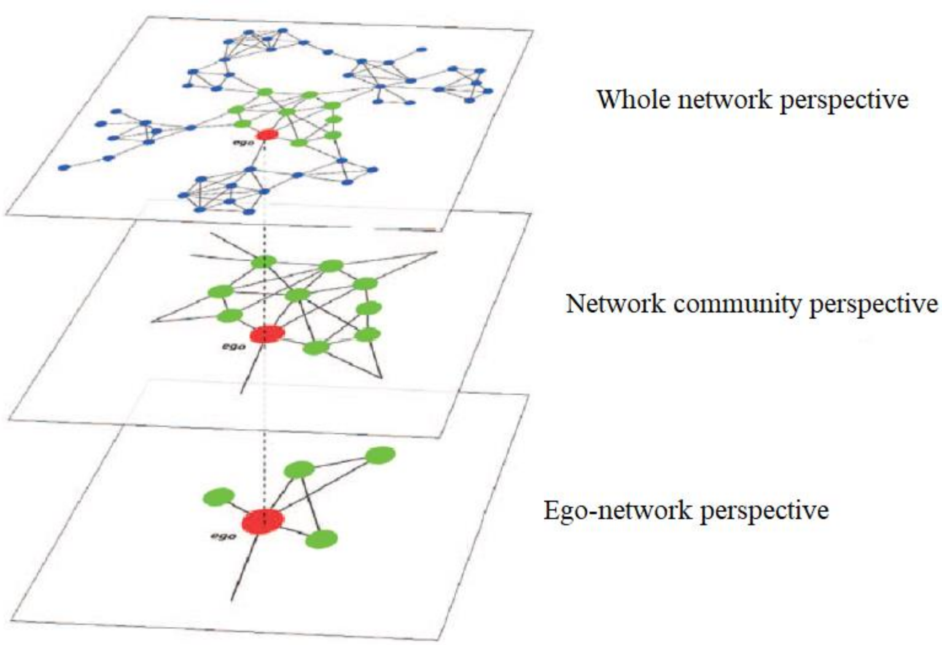

Figure 2. Understanding network perspectives

Source: Sytch and Tatarynowicz (2014)

	A1	A2	A3	A4	A5
A1	.	1	1	1	1
A2	1	.	0	0	1
A3	1	0	.	0	0
A4	1	0	0	.	1
A5	1	1	0	1	.

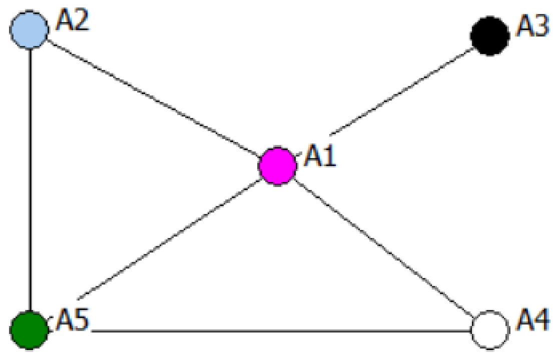

Figure 3. A simple undirected network

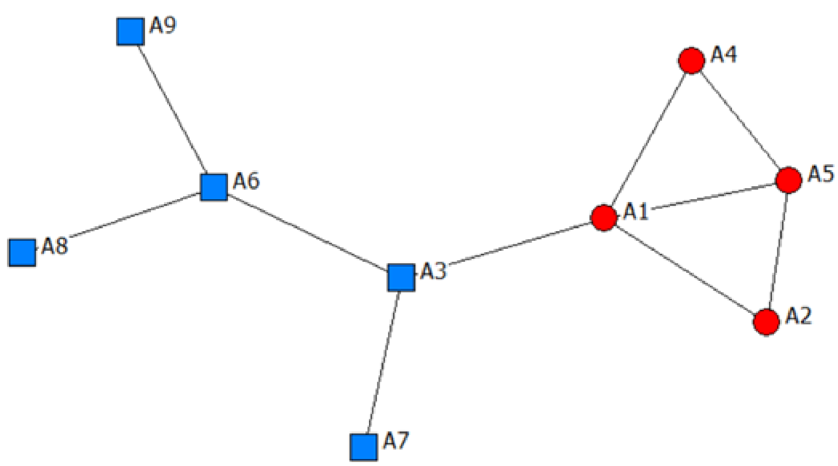

Figure 4. A simple undirected network with two communities

Table 1. Actor-level measures for top-20 firms by degree centrality

Firm	Degree	Constraint	Ego density	Eigenvector	Betweenness	Closeness
Microsoft Corp	82	0.016	0.004	0.957	0.593	0.306
Alphabet Inc	35	0.034	0.009	0.185	0.310	0.285
Dell Technologies Inc	20	0.092	0.047	0.165	0.152	0.280
Accenture PLC	17	0.066	0.008	0.042	0.203	0.263
SAP AG	17	0.061	0.015	0.152	0.229	0.292
Alibaba Group Holding	15	0.120	0.066	0.006	0.059	0.210
Amazon.com Inc	15	0.096	0.057	0.139	0.075	0.245
IBM Corp	15	0.080	0.029	0.027	0.056	0.232
Infosys Ltd	14	0.084	0.033	0.048	0.111	0.250
Tencent Holdings Ltd	13	0.108	0.064	0.022	0.071	0.232
Fujitsu Ltd	12	0.084	0.015	0.127	0.054	0.251
Tech Mahindra Ltd	12	0.083	0.000	0.108	0.041	0.237
Baidu Inc	11	0.185	0.133	0.005	0.034	0.202
Adobe Inc	10	0.103	0.022	0.117	0.058	0.238
Cisco Systems Inc	10	0.104	0.022	0.130	0.039	0.269
Facebook Inc	10	0.125	0.022	0.016	0.045	0.224
Gemalto NV	10	0.178	0.111	0.002	0.109	0.189
Lenovo Group Ltd	10	0.129	0.067	0.016	0.019	0.205
NEC Corp	10	0.142	0.044	0.004	0.045	0.204
Wipro Ltd	10	0.125	0.022	0.001	0.034	0.169

Table 2. Descriptive statistics and bivariate correlations

	Mean	SD	Degree	Constraint	Ego density	Eigenvector	Betweenness
Degree	2.306	4.355					
Constraint	0.790	0.307	-0.544				
Ego density	0.085	0.273	0.040	-0.087			
Eigenvector	0.022	0.055	0.696	-0.234	0.031		
Betweenness	0.008	0.034	0.939	-0.477	-0.043	0.666	
Closeness	0.185	0.038	0.316	-0.268	0.097	0.576	0.319

Appendix

Step 1: constructing a network of strategic alliances

In UCINET, data can be imputed in the edgelist format (*Data – Data editors – DL Editor* and then select *Edgelist1 (ego alter [value])* as data format).[2] As interorganizational ties are normally treated undirected, one has to select the *Undirected (force symmetry)* output option in the right panel of the *DL Editor* window (see Figure A1). One alternative way to input data would be in the *Piles (1-mode)* format (if the edgelist has not been already created), which can be particularly relevant to the interorganizational data. For example, while most strategic alliances are bilateral (i.e., have only two partners), some involve more than two collaborating parties (Lavie, Lechner, & Singh, 2007). The *Piles* format handles multiparty alliances by entering the names or identification numbers of alliance participants in one row. UCINET then creates all possible dyadic combinations of the participants of the alliance (Borgatti et al., 2002). The main component can then be identified by opening the following tab in UCINET: *Network – Regions – Components – Binary graphs*, where one can choose to extract the *main component vector* (see Figure A2). One can proceed to separate the sub-network in the main components by going at *Data – Subgraphs from partitions*, where the *Input Partition* field should contain the file with the main component vector, where the main component is assigned a value of 1 (see Figure A3).

-----INSERT FIGURES A1-A3 ABOUT HERE-----

Visualizing a network can be done through *NetDraw*—a package that is automatically installed with UCINET. Our network graph is depicted in Figure A4.

-----INSERT FIGURE A4 ABOUT HERE-----

Step 2: Deriving actor-level social network measures

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[2] Alternative formats of data inputting in UCINET 6 can be found at: https://sites.google.com/site/ucinetsoftware/how-to-use/faqs-tips/entering-data-using-the-dl-editor

UCINET 6 has separate tabs for ego-network *(Network – Ego Network)* and centrality *(Network – Centrality)* measures (see Figures A5 and A6).

-----INSERT FIGURES A5 and A6 ABOUT HERE-----

Network constraint is located under *Network – Ego Network – Structural Holes.* As can be seen in UCINET, there are two methods to compute the constraint variable. The first one assumes that ties beyond alters have no effect, as originally suggested by Burt (1992). The second method is to look at all of the alters' connections in the network, whether they are tied to ego or not. If the data on the whole network is available, the second method would involve more realistic inputs of alters' investment of time and energy in each other. Ego network density can be found under *Network – Ego Network – Egonet Density*.

Degree centrality is located under the centrality tab *(Network – Centrality – Degree)* since it is traditionally considered a centrality metric (Borgatti et al., 2018). Other centrality measures are also located under the same tab. Eigenvector centrality is found under *Network – Centrality – Eigenvector centrality*. There are different ways to normalize the measure we discussed earlier (in further analysis, we will use normalization to the maximum possible value). To obtain the usual betweenness centrality metric and its normalization (Freeman, 1979), we must select *Network – Centrality – Freeman Betweenness – Node Betweenness*. Finally, the tab to compute several closeness centrality metrics is found at *Network – Centrality – Closeness measures*. The routine produces Freeman's closeness centrality and normalization (Freeman, 1979), which we discussed earlier.

Step 3: Partitioning the network into network communities and calculating within-community density

In UCINET 6, we need to go to *Network – Whole networks & cohesion – Clustering Coefficient*. Among the reported statistics is the small world index, which is equal to 10.426 for the network in Figure A4. Recall that the network exhibits the small-world property when this index is greater than 1. We can then derive network communities through one of the community detection algorithms. The Girvan-Newman algorithm can be reached at *Network – Subgroups – Girvan-Newman*, while the multilevel algorithm (also known as the Louvain method of clustering) is available at *Network – Subgroups – Louvain method* (see Figure A7). The former algorithm has produced the community structure in Figure A8. Previously, we have mentioned that interorganizational research normally applies the Girvan-Newman community detection algorithm to a network's main component while considering the smaller components to be stand-alone communities (e.g., Sytch & Tatarynowicz, 2014).

-----INSERT FIGURES A7 and A8 ABOUT HERE-----

Within-community density can be obtained at *Network – Whole networks & cohesion – Density – Density by Groups*. Here, one needs to impute the original network dataset in the first row and the new file containing firm-community affiliations in the second row. The resulting output file will calculate the within-community density that can be used for further analysis.

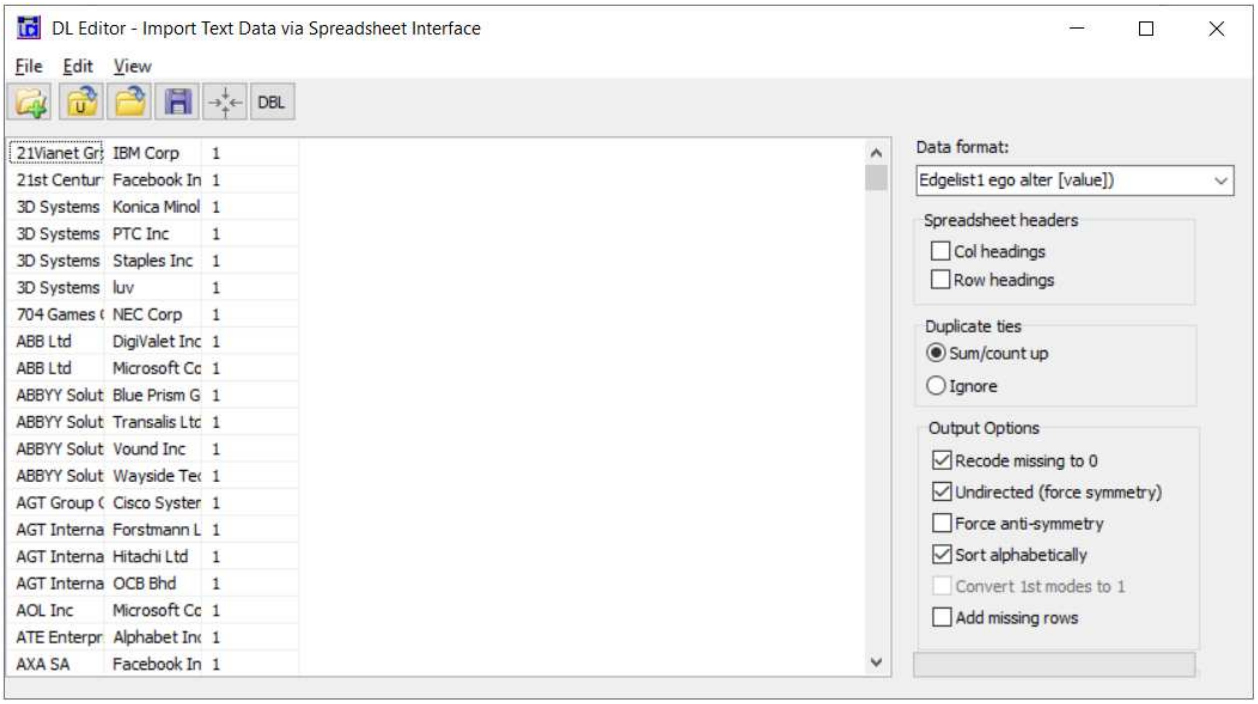

Figure A1. UCINET: Data inputting in the edgelist format

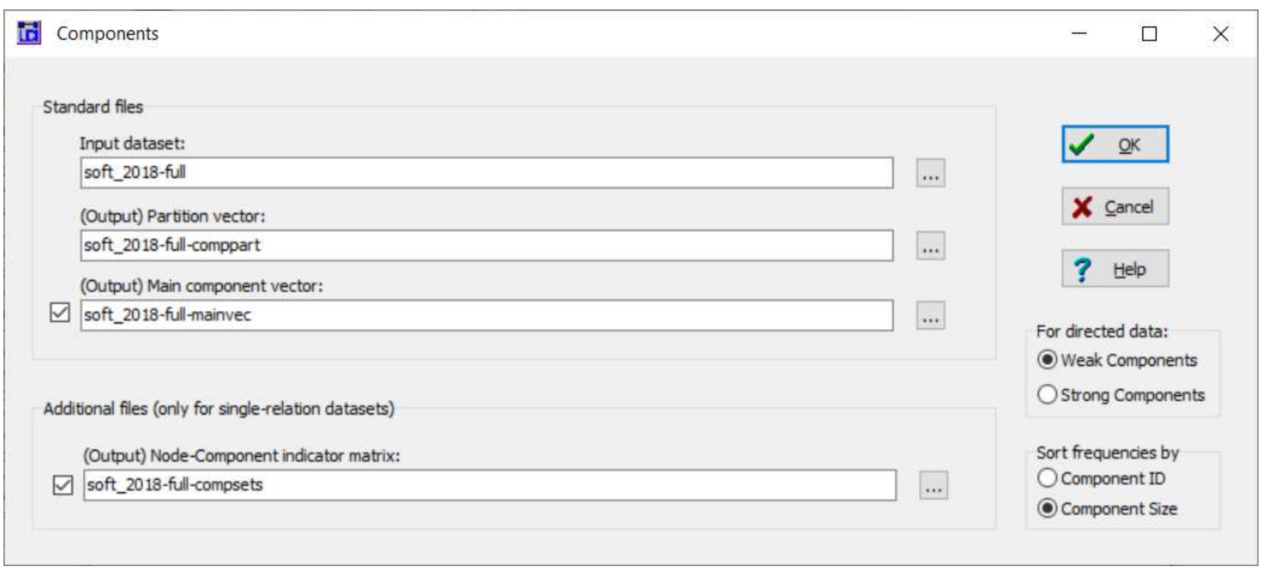

Figure A2. UCINET: Identifying network components

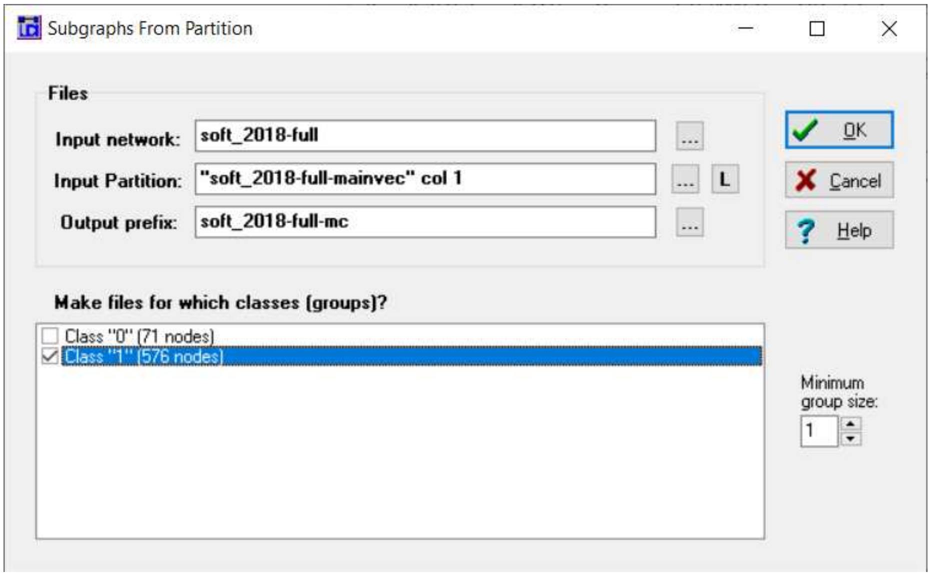

Figure A3. UCINET: Separating the network in the main component

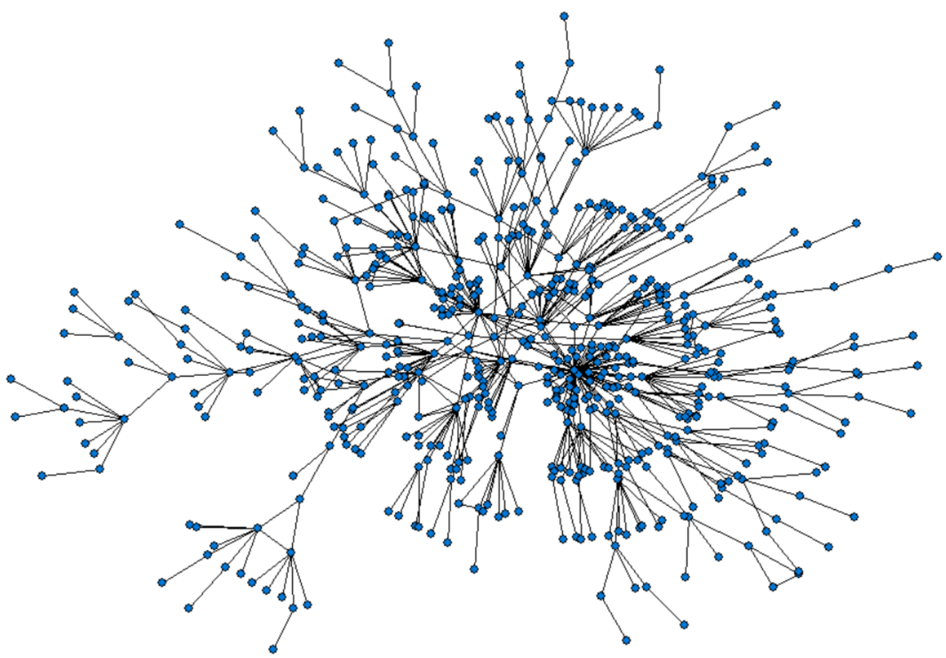

Figure A4. Structure of the main component in the global software industry in 2018

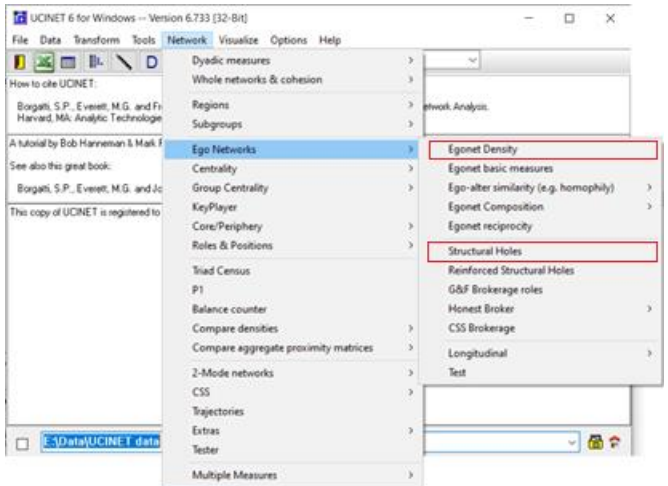

Figure A5. UCINET: Ego-network measures

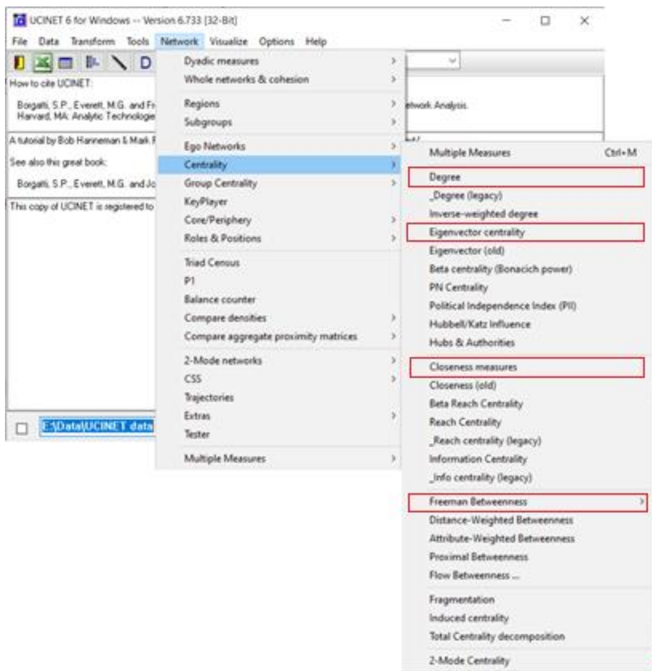

Figure A6. UCINET: Centrality measures

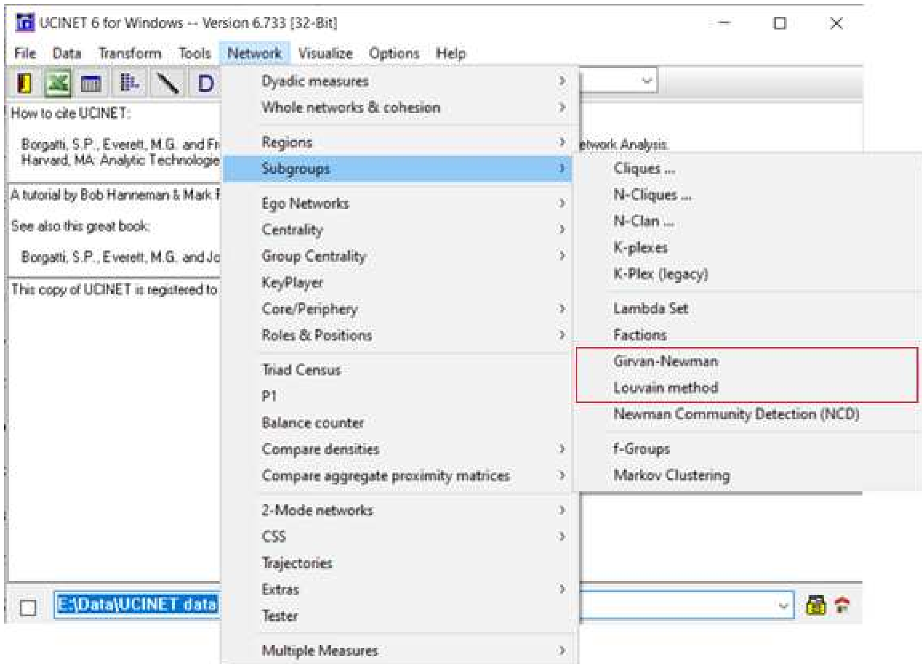

Figure A7. UCINET: Community detection algorithms

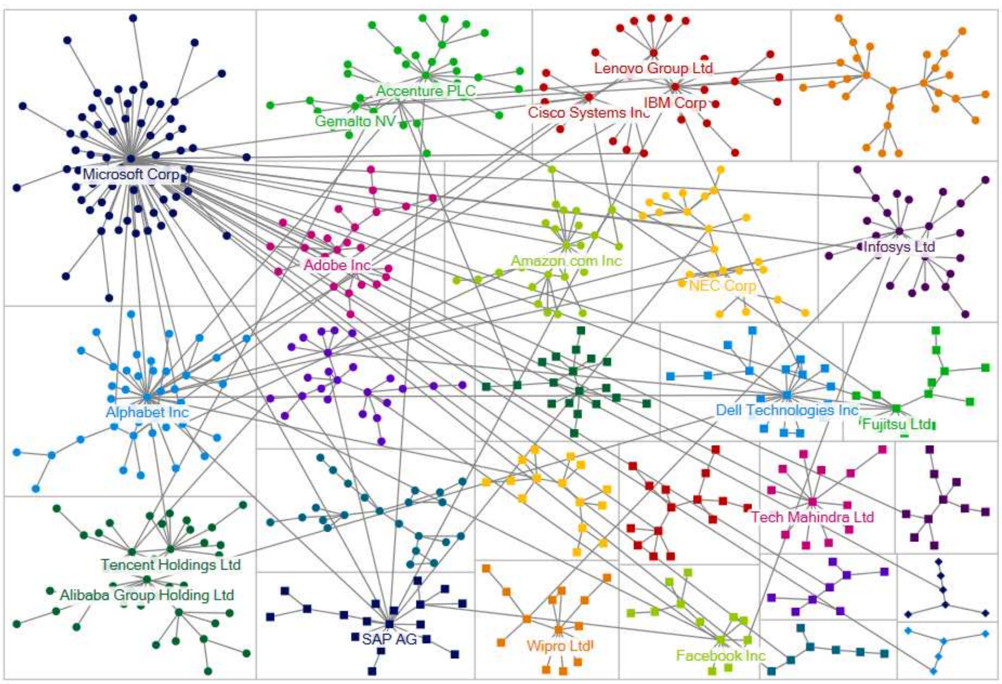

Figure A8. Community structure (names of top-20 firms by degree centrality are visible)