THE CASE FOR ADOPTING BLOCKMODELING IN HUMAN RESOURCE MANAGEMENT RESEARCH: EXAMPLES IN ANALYZING SOCIAL NETWORKS AND HRM SYSTEMS

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ABSTRACT

Blockmodeling is viewed often as a data reduction method. However, this is a simplistic view of the class of methods designed to uncover social structures, identify subgroups, and reveal emergent roles. Worse, this view misses the richness of the method as a tool for uncovering novel human resource management (HRM) insights. Here, we provide a brief overview of some essentials of blockmodeling and discuss research questions that can be addressed using this approach in applied HRM settings. Finally, we offer an empirical example to illustrate blockmodeling and the types of information that can be gleaned from its implementation.

Keywords: Organizational structure; inter-organizational networks; human resources; blockmodeling; clustering; social network analysis

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Human resource management (HRM) is concerned with the management of work and people, with a focus on outcomes, and is an integral part of any organization (Boxall, Purcell, & Wright, 2007). The human capital that employees represent is viewed as a source of competitive advantage (Coff, 1997) whose effective management can significantly enhance firm performance. However, given that certain boundary conditions may limit the sustainability of that advantage (Campbell, Coff, & Kryscynski, 2012), a more stable measure of human capital may be found in the exploration of the social structures – the complex array of interpersonal relationships among individuals in an organization.

Accordingly, a significant amount of attention has been directed at understanding how these internal social structures impact important organizational outcomes such as job satisfaction, motivation, citizenship behavior, performance, and turnover. However, the structure of these complex relationship webs can often be difficult to discern. Moreover, gathering and analyzing social structure data can be cumbersome and challenging. Individuals in an organization are not just connected to, and therefore influenced by, each other. Employees are also influenced by systemic factors – specifically, the HRM systems impacting them. Strategic HRM scholars have struggled with defining and analyzing HRM systems (Lepak, Liao, Chung, & Harden, 2006), as well as examining the influence of various HRM system components simultaneously. Here, we offer an overview of blockmodeling methods as one way to address the challenges of studying social and systemic organizational structures as they relate to HRM, with a particular emphasis on the possibilities for new avenues of exploration.

Social and systemic networks are made up of connections, or ties, between two individuals or an individual and another entity. For example, many scholars work with other scholars in the college or school of business at their university. Each of these relationships can be thought of as a "tie" between two individuals. Ties can be affective (e.g., ties resulting from friendship formation) or instrumental (e.g., ties resulting from coauthor relationships). Additionally, these individual scholars belong to a department or discipline. In this case, the "ties" are between the individual scholar and the department (i.e., the entity). The resulting web of relationships, or ties, is what makes up the social structure of the school or college of business. From this example, one can see that the social network can quickly become complex, and analyzing the network structure may prove cumbersome if utilizing traditional methods.

Blockmodeling is well suited to overcome these obstacles because, at its core, blockmodeling methods involve a substantively informed simplification of network structure. Blockmodeling is a class of methods for sorting individuals who are similarly connected in the social structure into well-defined clusters, called positions, after which the (less numerous) clusters can be examined rather than the (more numerous) individuals. Specifically, if two individual scholars from the above example have identical ties to other scholars in the college or school, they can be viewed as equivalent in terms of their social relationships. These two individuals would be grouped into the same "position." Moreover, each position has a related role with a variety of expectations regarding conduct. For instance, using the university system context, there are administrators, heads of departments, professors, and students that occupy positions. In this case, professors have general role expectations regarding students and *vice versa*. Rather than interpreting the relationships between and roles of individual employees, researchers can examine the relationships between the positions. The set of ties between positions form the blocks of a blockmodel. By shifting the focus from the complete set of actors and the full set of network ties to the clusters of actors and the resulting blocks, blockmodeling reduces complex social networks to smaller and more readily interpreted structures.

Since its inception based on the pioneering work of Lorrain and White (1971), systematic investigation of blockmodeling methods has received considerable attention in the social network literature. Applications of blockmodeling methods span multiple disciplines including sociology (White, Boorman, & Breiger, 1976), psychology (Arabie, Boorman, & Levitt, 1978), computer science (Airoldi, Blei, Fienberg, & Xing, 2008), statistics (Handcock, Raftery, & Tantrum, 2007), and physics (Karrer & Newman, 2011). Excellent reviews of blockmodeling methods are provided by Doreian, Batagelj, and Ferligoj (2005) and Goldenberg, Zheng, Fienberg, and Airoldi (2009). However, despite the moderate degree of popularity among methodologists in the organizational sciences, adoption, and application of blockmodeling methods remains relatively scarce in this discipline.

To support this claim, we utilized the "Business Source Complete" search engine to conduct a full-text search of the text string "social network" in eight major empirical journals in the organizational sciences (*Academy of Management Journal*, *Academy of Management Review, Administrative Science Quarterly, Journal of Applied Psychology, Organizational Behavior and Human Decision Processes, Organization Science, Personnel Psychology*, and *Strategic Management Journal)*. These searches yielded 2,124 hits in total. When this process was repeated using the text string "blockmodel," it yielded a mere 37 hits for these eight journals. Moreover, a closer examination of the articles using the term "blockmodel" revealed that, in all but eight instances, the term was found only in the title of an article in the References section (see, e.g., DiMaggio, 1986; Gerlach, 1992).

However, despite the underutilization of blockmodeling in the organizational sciences, the method offers researchers several advantages in addition to discerning fundamental network structure. First, while all social network data contains missing data with the potential to compromise results, blockmodeling permits inferences from incomplete data (Breiger, 1976; Nelson, 1986). In the case of actor non-response, there are effective methods for imputing missing data (by not discarding real data regarding the ties sent to non-respondents) that permit blockmodeling analyses (Žnidaršič, Ferligoj, & Doreian, 2012). Second, in research studying teams, centrality measures are commonly used in social network analysis as individual variables that are aggregated in subsequent statistical analysis. In contrast, blockmodeling provides a much more valuable assessment of subgroup identification in the form of positions and blocks that result from using blockmodeling methods designed to discover roles both extant and emergent (i.e., not previously identified). Third, while permutation testing is a common method for performing regression and correlation tests at the dyadic level, these tests do not facilitate subgroup identification. Although they also can be used to gauge the correspondence of whole networks, at best, they could assess the correspondence of partitions but only *after* they have been established. Fourth, blockmodeling can be used in conjunction with statistical techniques within a multi-method framework, increasing the robustness of the research designs and expanding subsequent empirical insights and substantive outcomes.

To illustrate the potential utility of blockmodeling methods, we offer the following scenario: Bolander, Satornino, Hughes, and Ferris (2015) examined whether politically skilled employees can place themselves into better locations in organizational social networks, which then vests them with greater power and influence, and ultimately increases performance and impacts other individual-level outcomes. These authors measured the political skill of respondents via self-reported items, collected social tie data to construct a social network and obtained centrality indexes for the respondents in this social network. They also collected objective sales performance measures from the organization. Although this approach worked for this study, suppose the authors wanted to examine the influence of social positions *and* social roles (Faust & Wasserman, 1992) to glean insights concerning the relationship between political skills and performance. Specifically, they could look to find emergent roles of individuals having certain relationships with others. Using blockmodeling, the authors would be able to reveal sets of actors (clusters) similarly embedded in this network to examine the expectations related to this configuration of social ties.

Understanding the impact of social roles, combined with individual-level social locations, could be a useful way of teasing apart contextual effects in salesperson performance beyond individual-level attributes, as well as predicting the likelihood of future connections between, and, within, identified positions and potential future social positions. In sum, although various analytic tools exist to examine relationships, such as the political skill-performance relationship, the relatively under-utilized method of blockmodeling in HRM research may provide important and new insights into contextual effects of organizations on behavior in the organizational sciences.

The underutilization of blockmodeling in the organizational sciences could stem from several sources. The most likely explanation could be a lack of familiarity with this approach. Accordingly, our intent here is to provide a description of blockmodeling and the use of blockmodeling in organizational contexts. In the next section, we outline some potential benefits of utilizing blockmodeling in applied research, and discuss several hypotheses. This is followed by a section presenting an example of blockmodeling applied in an organizational setting. The paper concludes with a summary.

UTILIZING BLOCKMODELING APPROACHES IN APPLIED RESEARCH

Blockmodels of networks may appear simple, but only if they are viewed merely as data reduction techniques. The information they contain, if *substantively directed*, represents the fundamental underlying structural characteristics of the original networks. Thus, blockmodeling offers a useful analytic approach for a variety of different research questions and objectives. In the following subsections, such uses are discussed by using relevant examples drawn from organizational research.

Data Reduction and Missing Data

One common application of blockmodeling techniques reduces a large network to a set of relationships between positions (Faust & Wasserman, 1992; White et al., 1976). The data reduction is accomplished via the use of a selected equivalence. Individuals are "equivalent" to the extent that they are connected to the same or similar other individuals. For example, referring back to our hypothetical college of business example: If Bob and Susan are both connected to Ron, Dave, Mike, and Sharon, they are structurally equivalent. Selected equivalences, in short, imply individuals exhibiting similar patterns of relationships in a social network can be placed in the same position (Faust & Romney, 1988). Using a specified equivalence, relationships between actors in a social network can be transformed to positional roles, facilitating the examination of hypotheses about how these positional roles (rather than those of individual actors) are related to, and impact, each other.

When producing such data reductions, four steps are necessary. First, the type of equivalence used to assign actors to positions is defined. While other more general equivalences have been defined (see Doreian et al., 2005), the most commonly used equivalence type has been structural equivalence. Structural equivalence concerns the extent to which individuals in the network exhibit ***identical*** ties to and from other actors (Faust & Romney, 1988), as in our previous example. In contrast, more general equivalences do not require identical ties to identical others, but rather involve structural ***similarity***, in which individuals exhibit similar patterns of social ties to similar (not identical) others. The selection of general equivalences may mitigate some concerns regarding missing single ties because actors with similar, but not identical, ties are clustered together (note, however, that structural equivalence is significantly more stable in the face of high non-response rates, while general equivalences are less so). These less restrictive definitions of equivalence, known as general equivalences, have been proposed as more accurately reflecting many real-world social contexts (Doreian et al., 2005; Faust & Romney, 1988). Moreover, there is sufficient evidence suggesting this idea is correct. However, the need to consider substantive issues when contemplating blockmodeling remains salient. A discussion on selecting equivalence is beyond the scope of this paper. However, we encourage readers to refer to the significant body of work by methodologists examining variations of equivalence (see Brusco & Doreian, 2015a, 2015b; Brusco, Doreian, & Steinley, 2015) to select the appropriate equivalence for their research endeavors).

Second, a measure of how well a constructed blockmodel fits the network data is needed. The direct approach to blockmodeling (Doreian et al., 2005) provides this capability for comparing different partitions of the same network using the *same* definition of equivalence. As with other methods (including structural equation modeling), there is often more than one well-fitting solution, or blockmodel. Thus, it is imperative that theory drives the selection of an appropriate choice of the equivalence type as well as the best fitting model. Moreover, different well-fitting blockmodel solutions can be interpreted together, because their interpretation, coupled with strong theoretical support, will complement each other (Doreian et al., 2005).

In the third step, equivalence representations are provided by assigning each actor to a cluster (position having an associated role) based on the selected equivalence. The relationships between clusters (blocks) are subsequently provided, describing how the positional roles are related to each other. These clusters are represented, most commonly, by a discrete model (but see Goldenberg et al., 2009, for a discussion of stochastic blockmodels), and the resulting blockmodel (often referred to as the image matrix) is the representation of the reduced network fitting under the selected equivalence.

In the fourth step, the adequacy of the positional analysis is assessed by some goodness-of-fit analysis in probabilistic models (see Faust & Wasserman, 1992, for descriptions of these steps). Ultimately, diverse ties in the observed network are reduced to a simplified relational model among roles, allowing for parsimonious models and interpretations of complex networks.

Blockmodeling has potential as an especially useful technique, particularly in the age of "big data," where social networks can be complex and difficult to analyze in their entirety because blockmodeling simplifies complex webs of relationship into succinct blockmodels, which reduces the number of data points analyzed by the researcher to a more manageable scale. To draw from a current example, Juniper Networks, a network infrastructure developer, uses LinkedIn to track the career trajectories of current, former, and potential employees, along with their skills, knowledge, and experience (Roberts, 2013). Using blockmodeling, Juniper might reduce the network of individuals into blocks based on general equivalence of skills, knowledge, experience, or prior employers (using two-mode data), where various employee archetypes (for current, past, or prospective employees) emerge. This data reduction allows for simplified role-based models that may provide important insights previously obscured by the idiosyncrasies of individual trajectories and skill/knowledge accumulation. Although "big data" contexts such as this represent a potential area of opportunity for blockmodeling analysis, it is important to note that substantively driven research questions must still direct the data collection and analysis to achieve valid results. Finally, there will be constraints regarding the size of networks being partitioned.

Identifying and Comparing Subgroups

A common application of blockmodeling is the identification of subgroups within a network. These subgroups often consist of a subset of individuals sharing ties among themselves, and may be described as cohesive. In an organizational context, the links between such subgroups can be used to assess information exchanges among them (Zack & McKenney, 1995), identify patterns of perceptions for members of an organization (Krackhardt, 1987), or predict the likelihood of convergence stemming from similar contextual factors (Borgatti & Foster, 2003). Once blockmodels are delineated, the densities (i.e., the proportion of actual relations within blocks relative to the possible number of relations, Wasserman & Faust, 1994) can give information regarding the individuals composing these positions (Faust & Wasserman, 1992; Jessop, 2003), and allow comparisons between positions using blocks serving as links between positions.

One way of interpreting blockmodels uses actor attributes (Faust & Wasserman, 1992). For example, a researcher could hypothesize that an individual team member's innovativeness can be used to interpret her structural position as a member in a certain organizational subgroup (e.g., decision-makers). The blockmodel could confirm or refute the hypothesis. If validated, one could then predict position and related outcomes for incoming new hires based on their innovativeness, thus establishing managerial relevance. This approach has been linked empirically to cooperation and identity confirmation (Milton & Westphal, 2005), interdependence (Nelson, 1986), and various performance outcomes attributable to the benefits or costs associated with group membership (e.g., Jessop, 2003, 2009).

More generally, one underused feature of the blockmodeling approach is its potential for validating structural theories – theories asserting that behavior is influenced by the configuration, frequency, and content of social ties

(Nelson, 1986). Therefore, inferences and predictions about behavioral outcomes can be made by examining the underlying social structure. For example, a researcher could hypothesize that more communication among members of a particular functional group, such as a Marketing department, is required for effective performance relative to another functional group, for example, an Accounting department. Using a blockmodel to identify functional groups, the researcher can refute or support the hypothesis by comparing densities within and between blocks and performance aggregates of the functional groups. See Doreian et al. (2005, Chapter 12) regarding substantively informed pre-specification of blockmodels.

Uncovering Network Structure

Idealized Structures

A research hypothesis could suggest an idealized blockmodel based on an organization's hierarchy or departmental structure (e.g., constituting a hypothesized structure of interactions) and this could be compared to a fitted blockmodel of the actual ties. Doreian and Conti (2012) showed how a blockmodel, based on structural equivalence of social relations formed in a Police Academy, was very close to the squad membership of the recruits, differing only in the location of one individual. Moreover, Thompson (1967) suggested disparities between the formal departmental structure and actual interaction structures could signal unrecognized organizational problems, or provide new insights into interdepartmental relationships.

Interdependencies

Interdependencies existing between the positions of a blockmodel may be due to pooled (or shared) destiny for their members, operational sequencing (e.g., the finished product of one serves as raw material for other), or reciprocal (highly dependent on others) interdependencies. By combining blockmodel results with the identification of the interdependence between the identified blocks, managers have tools to structure (or restructure) their organizations and departments to operate more efficiently. For instance, Woodward (1965) demonstrated the moderating effect of production objectives (e.g., small-batch, mass production, etc.) on patterns of interaction between Marketing, Product Development, and Production departments. She concluded that organizational interaction structures differ under different technological conditions. Small-batch production objectives resulted in intense interaction between the departments, whereas mass production resulted in frequent but not constant interaction, and a production focus by the organization resulted in interactions that were episodic and infrequent.

Evaluating Human Resource Management Systems

Related to the idea of "shared destiny," another intriguing application of blockmodeling methods to HRM concerns may be found in the challenge of defining and analyzing HRM systems. A concrete definition of HRM systems was proffered by Lepak, Hui, Yunhyung, and Harden (2006, p. 221), who asserted that, generally, an HRM system is "a bundle of HR practices or HR policies oriented toward some overarching goal." Concrete definitions of HRM systems have been more elusive, and the resulting examinations raise questions regarding the interactions between various systems and how they influence employees. For example, are control and high involvement HRM systems additive, multiplicative, or neither? Blockmodeling can offer some insight into addressing this question by allowing HRM scholars to compare equivalent individuals who might be subject to different HRM systems, and variations in outcomes such as commitment, performance, or turnover can be evaluated.

Succession Planning

Another potential use for blockmodeling techniques is to employ these methods to identify a successor in succession planning. Structurally equivalent individuals are assumed to have similar access to resources embedded in the social network (Wasserman & Faust, 1994), as well as similar reputations and social capital. Using a blockmodeling method to identify a subgroup of equivalent individuals, a researcher may identify a subgroup consisting of leaders and potential leaders who share similar structural characteristics and attributes, but who do not yet have leadership roles. Most likely, such an analysis will require multiple methods to test the hypotheses that structural equivalence with an existing leader indicates leadership potential. We discuss the role of blockmodels in multi-method research studies in the next section.

Multi-Method Analyses

Additionally, blockmodeling has promise in multi-method analysis. When coupled with traditional hypothesis testing techniques, blockmodeling can be used to assess the effects of multiple dimensions of the social structure simultaneously (Gerlach, 1992). For example, Burt's (1976) typology (of isolates, sycophants, brokers, and primaries) could be utilized by a researcher to shed light on the interaction among various roles individuals hold within organizations. Suppose, for example, a researcher collected network ties (e.g., friends and advisors), attribute data (e.g., innovativeness), and outcomes (e.g., job satisfaction or organizational commitment) for a large, complex organizational network. Using blockmodeling, the researcher could identify the multiple roles an individual occupies on several dimensions of the organizational network. For instance, an individual (and those in the same identified position) may be serving in a sycophant role (having more ties to members of other positions than to themselves and not receiving many ties within the friendship network). In turn, during project interactions, the same individual could occupy the role of a primary contributor (receiving many ties from members of other positions as well as from their own members). In advice networks, the same individual might be an isolate (neither sending nor receiving ties from other positions). See Wasserman and Faust (1994) for a more extended discussion of positions and roles.

It is important to note that, as with most analytical techniques, nonsensical or inaccurate solutions can result from poor initial choices regarding the blockmodel. Therefore, to provide a valid blockmodel solution, the choices defining the criteria for selecting a blockmodel analysis must be driven by theory. In the example above, Burt's (1976) typology provides some guidance on the number of positions for the blockmodel solution.

Some obvious research questions arise from the scenario above. How do roles interact to impact individual and collective outcomes? Does one role mediate the effects of other roles, or does one role moderate the effects of other roles? These interactions may help explain variance in outcomes unaccounted for by analyzing only a single dimension of the social structure. A researcher could use individual interaction data to uncover structural positions (e.g., isolates, sycophants, brokers, and primaries) and use this blockmodel outcome, together with actor attributes, as inputs to a regression or structural model for testing relations between individuals' roles and their individual attributes on collective or organizational outcomes. In the next section, we provide some examples of research questions that may be appropriate to examine with the use of blockmodeling.

Examples of Research Questions

Based on some of the above uses of blockmodeling in the organizational sciences, many types of research questions can be studied and hypotheses derived. For example, at a basic level, researchers may be interested in the identification of subgroups of actors who are similar with respect to their location in the network. In general, associated hypotheses may take the form of: groups similar in terms of structural attributes will exhibit different patterns of interactions than those of groups having different structural attributes.

Additionally, for inter-organizational networks, it is likely that the network structure will have a core-periphery form. Blockmodeling allows for a clear specification of alternative core-periphery structures characterized by a core subgroup of individuals and a group of loosely connected peripheral members (Borgatti & Everett, 1999). Based on a well-defined core-periphery structure, hypotheses regarding the impact of core-periphery structures can yield information on how the roles of a group of more prominent actors relate to the roles of less prominent actors in a network. See, for example, Wasserman and Faust (1994, Figs. 10.7 and 10.8). The idea of a core-periphery structure can be extended to one having multiple cores and multiple peripheries. Kronegger, Ferligoj, and Doreian (2011) provide an example in a different substantive context. They studied collaborative ties among Slovene scientists using blockmodeling methods. Multiple cores were identified in the system of ties, each having their own periphery. There were also some bridging ties between cores, a structural feature that had not been identified previously in scientific collaborative networks. One also could consider whether the subgroups formed from the blockmodeling of a social network comport with some a priori hypothesized structure (e.g., an organizational hierarchy or division into working teams).

Another potential area of interest for HRM researchers involves the comparison of subgroups formed by blockmodeling with clusters obtained based on an exogenous set of attributes. For example, Totterdell, Wall, Holman, Diamond, and Epitropaki (2004) compared the results of a blockmodeling analysis of worker ties to the clusters obtained from a partition based on job affect measures. Using this comparison, these authors determined that the presence of work ties and structural equivalence impacted similarity of affect between employees, supporting a hypothesis based on emotional contagion.

Similarly, a testable hypothesis using blockmodeling as part of a multi-method study is: will membership in group X (established through positional assignment) increase an outcome Y (e.g., performance, satisfaction) though some social mechanism (e.g., higher cooperation). For example, Milton and Westphal (2005) found, after controlling for conventional social network positions, a positive association between structurally equivalent positions in identity confirmation networks and cooperation. This suggests that, beyond individual-level structural factors, roles provide additional explanatory power, reflecting a strength of blockmodeling techniques via the identification of structurally equivalent positions. Of course, other equivalence types (Doreian et al., 2005) could be considered depending on organizational contexts.

Finally, given that networks can change over time, the longitudinal analysis of networks raises a variety of interesting questions. For example, how does subgroup structure change over time? One approach to studying this problem is to define time slices (Batagelj, Doreian, Ferligoj, & Kejžar, 2014) to examine successive time slices for structural change. For instance, if one or more key members leave (or join) the network, how does that affect the subgroup structure? And how do roles change in multidimensional time-evolving networks? This could be particularly useful to HRM scholars concerned with the stability of social capital embedded in organizational network structures when individuals leave an organization.

In short, blockmodeling facilitates the provision of computationally feasible and interpretable results considering both individual and social structural features of organizational contexts and inter-organizational networks. Moreover, blockmodeling is not one single standardized method. Rather, it is a set of methods depending on the nature of the data analyzed and the substantive concerns of the researcher. Some of these concerns are illustrated in Fig. 1. One concern is whether the network data are one-mode (only one type of unit is involved, e.g., individuals of an organization) or two-mode (involving two types of units, e.g., individuals and projects where ties are participation of individuals in projects). This criterion is in the second row of the figure. Network data, both one-mode and two-mode, can be unsigned or signed. White (1961) provided an early example of signed one-mode data for managerial conflict within an organization. A potential example for two-mode signed organizational data involves individuals and proposals for changing organizations, with the signs being support or opposition to proposals.

On the left in Fig. 1, there are two general blockmodeling approaches for partitioning signed data that depend on which theoretically driven model is fitted. For unsigned data, a core distinction is whether the ties are undirected or directed. When the ties are undirected, then the corresponding network matrix is symmetric. Directed ties, however, typically yield asymmetric network matrices. For some directed networks, it is possible to partition them as two-mode data. In inter-organizational networks where the ties are flows of products between organizations, it is often useful to partition the rows (as producers) and the columns (as consumers) differently (but at the same time). There is another distinction regarding data that is not included in Fig. 1 to keep the

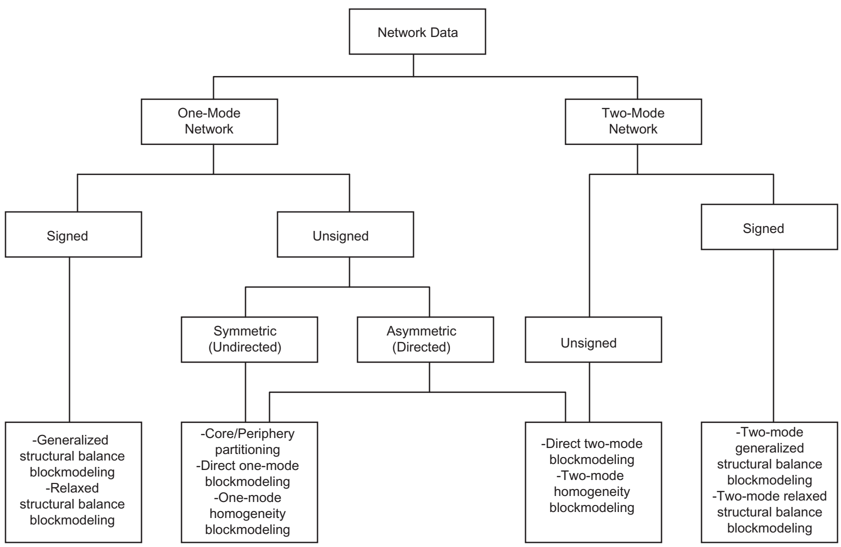

Fig. 1. A Conceptual Overview of Data Characteristics and Blockmodeling Methods.

figure simple. For both signed and unsigned data the ties can be binary (they exist or not) or valued (have some strength). In the bottom row, there are four broad categories of data analytic methods within blockmodeling. The homogeneity methods are particularly useful for valued networks. As the data we examine below are unsigned, readers interested in signed data are referred to Doreian and Mrvar (1996, 2009).

In the next section, we walk through an empirical example to illustrate the steps and issues associated with the utilization of blockmodeling in an HRM research context.

A BLOCKMODELING EXAMPLE

Organizational Data and Research Questions

To facilitate understanding about how an HRM scholar might utilize these methods, we provide the following example to illustrate the application of blockmodeling. In this example, we use network data collected from a small creative firm in a large southeastern urban center. Network data were obtained from $n = 16$ employees using the full roster method (Wasserman & Faust, 1994) for two distinct relations. Each employee was given a list of other full-time employees in the firm and asked to identify those employees whom they considered as friends (the friendship relation) and those with whom they would like to collaborate on a project (the collaboration relation). Although the collaboration network is of particular importance in our example, the friendship network is analyzed also.

For both relations, employees were asked to indicate the strength of the tie on a scale of $1 =$ low to $3 =$ high. The resulting data were arranged into two 16×16 asymmetric network matrices (one for friendship and one for collaboration) with elements ranging from 0 (no tie) to 3. The network friendship and collaboration matrices are displayed in Tables 1 and 2, respectively. In addition to these networks, data were also obtained for each employee for several attributes. These attributes included team, individual, and overall job performance ratings from the supervisor, as well as measures on each of the big-five personality traits (Digman, 1990; Goldberg, 1990).

We had the following research questions:

(1) What is the nature of the subgroup structure for the collaboration network?
(2) Is the subgroup structure for the collaboration network similar to that of the friendship network (this would imply that the latter is a good surrogate for the former)?

Table 1. The Friendship Network Matrix.

	A	B	C	D	E	F	G	H	I	J	K	M	N	O	P	Q
A			2								1				2	
B				1				2	1		1					
C	2	2			1				1		1				2	
D											2	2				2
E																
F									2	2	3		2			
G									1	2	2					
H	3	1		2	3	2			2	1	3	2	1	1		2
I	2	1			1			2		2	3		2	2		
J		1		2	2	3	2	3	2		3	2	3	2		1
K	1	1		1					3	1			2			
M				2				1					2			
N											3					
O	3	3	3	3	3	3	3	3	3	3	3	3	3		3	3
P	2		1					1	1		1					
Q	1			3				2	1		3	3		2		

Notes: The tie values range from 1 to 3 with larger values indicating a stronger tie. Zeros are omitted from the table to improve readability.

(3) Is there a strong relationship between the collaboration subgroup structure and job performance ratings for each individual?
(4) How does the subgroup structure in the collaboration network correspond to personality characteristics?

Blockmodeling was implemented to help address these four research questions. Note that the research questions came before the decision to implement blockmodeling, as it is best used as a substantively driven method.

Selection of a Blockmodeling Method

For the data in Tables 1 and 2, it is clear we are dealing with *one-mode* networks for both the friendship and collaboration relations. Two-mode networks correspond to two sets of objects, such as a set of CEO's and the set of corporations for which the CEO's serve on the board of directors (Galaskiewicz, 1985; Wasserman & Faust, 1994). From Fig. 1, we next ascertain that the two networks are *unsigned*: all collaboration network ties are non-negative, as are the friendship ties. Signed data (with both positive and negative elements in the network matrix) would have arisen if employees had also been asked to identify

Table 2. The Collaboration Network Matrix.

	A	B	C	D	E	F	G	H	I	J	K	M	N	O	P	Q
A		1	3		2			2					3		3	
B	1		2		3			3	1		2		2	3	1	
C	1	2			2			3					3		1	
D		2						2			2	3				
E	2	2	1	1				3	2		3	1	3		2	1
F	3	1	2	1	2			3	3		3	2	3	1	2	
G	1	1	3	3	3			3		2	3	2	3		3	
H	2	1			2						3	1	3	1		
I	2				3			3			3		2	2		
J	2	2	1	2	2	3	1	3	2		3	2	3	2	1	2
K	1				3			3					2	2		
M	3		2	3				3	1						2	3
N	3		3					3			3			3	3	
O	3	3	3	3	3	3	3	3	3	3	3	3	3		3	3
P	2		1					2								
Q	3	2	2	3		2	2	3	2	2	3	3		3	2	

Notes: The tie values range from 1 to 3 with larger values indicating a stronger tie. Zeros are omitted from the table to improve readability.

those co-workers with whom they did not want to collaborate. Clearly, the networks are *asymmetric* (as the networks are *directed*). Person A might seek a collaborative tie with person B at a high level of three while B might not seek collaboration with A at all (or, perhaps, to a lesser degree).

The branches stemming from the "asymmetric (directed)" box of Fig. 1 lead to either one- or two-mode methods at the bottom of the diagram. We posit for asymmetric ties that two-mode blockmodeling is worth considering because of its flexibility to accommodate two different subgroup structures for the employees: (i) one in their role as collaboration *consumers* (seekers of collaboration with others), and (ii) one in their role as collaboration *producers* (being sought after for collaboration with others). Thus, even though friendship and collaboration networks are inherently one-mode, we analyze them using a two-mode procedure to differentiate between the roles of collaboration consumption and collaboration production. The blockmodeling tool that we selected for our analyses of this network is two-mode homogeneity blockmodeling.

Homogeneity blockmodeling has a long-standing history in both the classification (Hartigan, 1972) and social network (Borgatti & Everett, 1992; Žiberna, 2007, 2009) literatures. Succinctly, the goal in two-mode homogeneity blockmodeling is to obtain the partitions that maximize block/submatrix homogeneity with respect to the elements they contain (a perfectly homogeneous block would be one where all the elements are the same). The two-mode homogeneity blockmodeling approach that we employ has recently received considerable attention (Brusco & Doreian, 2015a, 2015b; Brusco et al., 2015; Brusco & Steinley, 2007; Van Rosmalen, Groenen, Trejos, & Castillo, 2009).

The method establishes two distinct partitions of the employees: (i) a partition of the employees into K clusters to capture their role as collaboration consumers, and (ii) a partition of the employees into L subgroups to discern their role as collaboration producers. The K clusters of collaboration consumers and L clusters of collaboration producers jointly form blocks, or submatrices, of the collaboration network matrix. A precise criterion was applied to calculate a pseudo R^2 type of measure, commonly referred to as variation-accounted-for (or *vaf*). Moreover, we adopted the typical practice of ignoring all main diagonal elements of the network matrix in the computation of means and sum-of-squares, which is appropriate in our context because employees do not collaborate with themselves or identify themselves as friends.

Many authors have developed exact and approximate (or heuristic) solution procedures for the two-mode homogeneity blockmodeling problem (which is sometimes described more generally as a two-mode partitioning problem) that we consider. We employ the two-mode K-means heuristic for our analyses. The two-mode K-means algorithm (Baier, Gaul, & Schader, 1997) is among the most popular of the heuristic procedures. The two-mode K-means heuristic is fast, scalable for at least several hundred actors (possibly into the thousands), and has repeatedly proved to be effective at recovering the underlying true subgroup structure in simulation experiments (Brusco & Doreian, 2015b; Brusco & Steinley, 2007; Van Rosmalen et al., 2009).

Model Selection

Now that two-mode homogeneity blockmodeling has been identified as an appropriate blockmodeling tool for this application, one additional issue must be resolved. Specifically, there must be some mechanism in place for model selection, which is effectively defined here as the appropriate choices for K and L (i.e., some type of stopping rule is required). In this paper, we adopt a model selection process for multimodal cluster analysis known as the convex hull (or *CHull*) method, which has been shown to be effective in a variety of previous studies (Brusco et al., 2015; Ceulemans & Van Mechelen, 2005; Schepers, Ceulemans, & Van Mechelen, 2008; Schepers & Van Mechelen, 2011; Wilderjans, Depril, & Van Mechelen, 2013). An extensive overview of the *CHull* method is provided by Wilderjans, Ceulemans, and Meers (2013).

The process begins by running the algorithm for all combinations of K and L associated with the intervals $K_1 \leq K \leq K_2$ and $L_1 \leq L \leq L_2$. The typical selection is for $K_1 = L_1 = 2$. The values of K_2 and L_2 may depend on n;

however, $K_2 = L_2 = 8$ is a reasonable maximum for most applications. The complexity of a model is defined as the total number of clusters, $\xi = K + L$. So, for example, models where ($K = 3$, $L = 3$), ($K = 2$, $L = 4$), and ($K = 4$, $L = 2$) would all have the same complexity as defined here.

Once the solutions and *vaf* values have been obtained for all combinations of K and L, the next step is to produce a deviance plot (see Figs. 2 and 4), which consists of model complexity ($\xi = K + L$) on the horizontal axis and *vaf* on the vertical axis. The upper boundary of the convex hull is established by drawing line segments that connect the maximal *vaf* values for the different levels of complexity (ξ). Only those solutions on the upper boundary of the convex hull of the deviance plot are retained for further consideration. The number of solutions on the upper boundary is denoted as B. We apply the notation *vaf* (b) and $\xi(b)$ to refer, respectively, to the *vaf* and model complexity for solution b ($1 \leq b \leq B$).

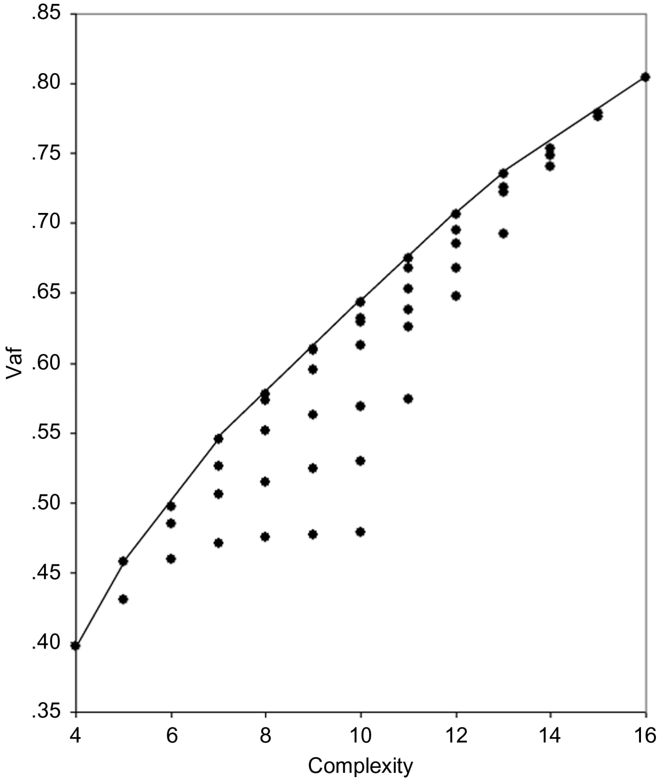

Fig. 2. Deviance Plot of Homogeneity Blockmodeling Results for the Collaboration Network.

The final step is to select one of the *B* solutions from the upper boundary of the convex hull. This can be accomplished via a visual inspection of the deviance plot, whereby clear elbows in the plot are identified to select a solution in the same manner as a scree plot in factor analysis. Alternatively, Ceulemans and Van Mechelen (2005) have offered two measures corresponding to the slopes of segments of the convex hull. The first of these is a difference measure, *Diff*CH. The second measure is an index pertaining of the ratio of the difference on the left to the difference on the right. Although less subjective than visual inspection of the deviance plot, the *Diff*CH and *Ratio*CH measures are not without some drawbacks. The primary limitation of the *Diff*CH measure is that there in a natural propensity to see the larger differences at the lower levels of model complexity and, accordingly, there is a tendency for the *Diff*CH measure to have some bias toward smaller values of complexity, ξ. The primary limitation of *Ratio*CH is its sensitivity to very small changes in the *vaf*. In their comparative analyses, Ceulemans and Van Mechelen (2005) found that *Ratio*CH performed better than *Diff*CH; however, we will adopt the practice recommended by Brusco et al. (2015) and consider both measures in the model selection process in conjunction with a visual assessment of the deviance plot.

Implementation and Results

We implemented two-mode homogeneity blockmodeling in MATLAB using the `tmklmp_nodiag.m` program developed by Brusco et al. (2015). This program runs 500 restarts (given the use of a heuristic) of the two-mode *K*-means heuristic to produce a set of solutions. The partitions associated with the restart that provides the best *vaf* value are stored along with the values of *vaf*. We applied the `tmklmp_nodiag.m` program to both the friendship and collaboration networks for all combinations of *K* and *L* on the intervals $2 \leq K \leq 8$ and $2 \leq L \leq 8$.

The deviance plot for the collaboration network is displayed in Fig. 2. This plot shows the *vaf* values for all 49 combinations of *K* and *L*, the horizontal axis is the level of complexity of the model, $\xi = K + L$. Some levels of complexity do not even produce a solution on the upper boundary of the convex hull and, therefore, can be excluded from further consideration. There is a modest elbow at $\xi = 5$. This is supported by the fact that $\xi = 5$ produces the largest *Diff*CH and *Ratio*CH measures, as shown in Table 3. Therefore, we selected $\xi = 5$ as the level of complexity and the solution on the upper boundary of the convex hull for this level of complexity, which corresponds to $K = 3$ and $L = 2$. The resulting blockmodel is shown in Fig. 3.

Research Question #1: The Nature of Subgroup Structure

Regarding research question #1, which asks about the nature of the subgroup structure, one conclusion is immediately evident: There is a substantial

Table 3. Model Selection Results for the Collaboration Network.

ξ	*vaf*	*Diff*CH	*Ratio*CH
4	0.39688		
5	**0.45812**	**0.0177**	**1.41**
7	0.54521	0.0109	1.34
10	0.64301	0.0006	1.02
11	0.67503	0.0007	1.02
12	0.70634	0.0025	1.09
13	0.73514	0.0057	1.25
16	0.80433		

Notes: For each level of complexity that produced a solution on the upper boundary of the convex hull in Fig. 2, the *vaf* value is reported. The row corresponding to the maximum *Diff*CH and *Ratio*CH measures is highlighted in bold.

Producers

Consumers	H	A	E	K	N	C	P	B	D	F	G	I	J	M	O	Q
J	3	2	2	3	3	1	1	2	2	3	1	2		2	2	2
O	3	3	3	3	3	3	3	3	3	3	3	3	3	3		3
Q	3	3		3		2	2	2	3	2	2	2	2	3	3	
A	2		2		3	3	3	1								
B	3	1	3	2	2	2	1					1			3	
E	3	2		3	3	1	2	2	1			2		1		1
F	3	3	2	3	3	2	2	1	1			3		2	1	
G	3	1	3	3	3	3	3	1	3				2	2		
N	3	3		3		3	3								3	
C	3	1	2		3		1	2								
D	2			2				2						3		
H		2	2	3	3			1						1	1	
I	3	2	3	3	2										2	
K	3	1	3		2										2	
M	3	3				2	2		3			1				3
P	2	2				1										

Fig. 3. The $K = 3$, $L = 2$ Homogeneity Blockmodel for the Collaboration Network.

difference between the subgroups for collaboration consumers and collaboration producers. The producers separate into two subgroups of roughly equal size. The first subgroup consists of seven employees {H, A, E, K, N, C, P} who are relatively highly sought after as collaborators, whereas the second subgroup of nine employees {B, D, F, G, I, J, M, O, Q} are sought out far less often. By contrast, the consumers are classified into three very different subgroups. The first of these is a small subgroup {J, O, Q} consisting of employees who sought collaboration with just about everyone else. However, none of these three employees is in the producer cluster of those that were heavily sought after as collaborators. The second subgroup of consumers, {A, B, E, F, G, N}, consists of six employees who sought collaboration most strongly with the first subgroup of producers but not the second. Finally, the third subgroup of consumers, {C, D, H, I, K, M, P}, is comprised of individuals who modestly sought collaboration with the first group of consumers, but not at all with the second.

Overall, the results for the collaboration network indicate the importance of adopting a two-mode perspective because the subgroup structures for collaboration consumers and producers are very different. Some employees (J, O, Q} heavily sought collaborators, but are not heavily sought after. Some employees {A, E, N} heavily sought others and were also heavily sought after. Some employees did not heavily seek {C, H, P}, but were still quite heavily sought after. Finally, some employees {D, I, M} did not heavily seek collaborative partners nor were they heavily sought after. Disentangling the collaboration consuming and producing behavior is more clearly revealed by using the two-mode perspective.

Research Question #2: Similarity Between Collaboration and Friendship Subgroup Structure

Table 4 reports the *vaf*, *Diff*CH and *Ratio*CH values for the friendship network. The deviance plot for the friendship network looks almost identical to that of the collaboration network. It is shown in Fig. 4. Based on the deviance plot, the *Diff*CH, and *Ratio*CH values, there is a clear case for selecting $\xi = 5$. As was the case for the collaboration network, the solution on the upper boundary of the convex hull of the deviance plot for $\xi = 5$ corresponded to the solution for $K = 3$ and $L = 2$. The resulting blockmodel is displayed in Fig. 5.

Although the results for the friendship and collaboration networks suggest the same levels of ξ, K, and L, there are profound differences in the partitions. For example, the friendship producer subgroups are {K, I, N, H, A, D, E, M, O} and {B, C, F, G, J, P, Q}. To translate this to the collaboration partition, employees {D, O, I} and {C, P) would have had to be moved between clusters. Even greater disparity between the friendship and collaboration solutions is exemplified by the partition of friendship consumers, where employee Q is in a subgroup by itself, and the other two clusters vary substantially in size. Therefore, the succinct answer to research question #2 is that there is little correspondence between the friendship and collaboration results and, accordingly, the former does not serve as a good surrogate for the latter.

Research Questions #3 and #4: Relationship between Collaboration Subgroup Structure and Personality and Job Performance

The subgroup memberships associated with the blockmodeling analysis of the collaboration network were produced by an algorithmic process and, therefore,

Table 4. Model Selection Results for the Friendship Network.

ξ	*vaf*	*Diff*CH	*Ratio*CH
4	0.40485		
5	**0.49755**	**0.0372**	**1.67**
6	0.55300	0.0113	1.26
8	0.64136	0.0130	1.42
9	0.67251	0.0002	1.01
11	0.73443	0.0051	1.20
12	0.76030	0.0068	1.36
13	0.77938	0.0010	1.05
16	0.83365		

Notes: For each level of complexity that produced a solution on the upper boundary of the convex hull in Fig. 2, the *vaf* value is reported. The row corresponding to the maximum *Diff*CH and *Ratio*CH measures is highlighted in bold.

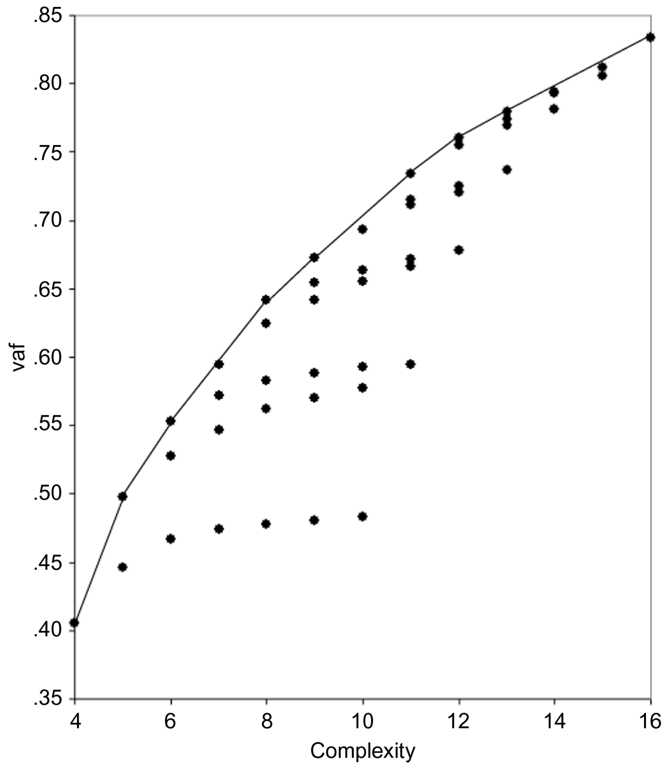

Fig. 4. Deviance Plot of Homogeneity Blockmodeling Results for the Friendship Network.

Consumers \ Producers	K	I	N	H	A	D	E	M	O	B	C	F	G	J	P	Q
O	3	3	3	3	3	3	3	3		3	3	3	3	3	3	3
H	3	2	1		3	2	3	2	1	1		2		1		2
I	3		2	2	2		1		2	1				2		
J	3	2	3	3		2	2	2	2	1		3	2			1
Q	3	1		2	1	3		3	2							
P	1	1		1	2						1					
B	1	1		2		1										
A	1										2				2	
C	1	1			2		1			2					2	
F	3	2	2											2		
G	2	1												2		
K		3	2		1	1				1				1		
M			2	1		2										
D	2							2								2
E																
N	3															

Fig. 5. The $K = 3$, $L = 2$ Homogeneity Blockmodel for the Friendship Network.

should not be treated as observed data. However, to complement other hypothesis testing methods, the subgroups can be examined to identify differences among them with respect to salient attributes. This is the approach we adopted to address research questions #3 and #4. Table 5 reports, for each subgroup of producers and consumers associated with the collaboration network, the mean ratings on team performance, individual performance, overall performance, and each of the big-five personality measures.

Table 5 reveals that the producer subgroup 1 {H, A, E, K, N, C, P} has higher mean ratings for team, individual, and overall performance ratings than the other producer subgroup. Considering the small sample sizes involved, it was somewhat surprising to observe that independent samples *t*-tests detected significant differences between the two producer subgroups for team ($p < 0.01$), individual ($p < 0.05$), and overall ($p < 0.01$) performance. The results of the significance tests were unaffected by the assumption of equal/unequal variances. Overall, the implication of the evaluation of the producer subgroups with respect to performance suggests that a plausible explanation for the emergence of a subgroup of highly sought-after collaborators, {H, A, E, K, N, C, P}, stems from the fact that others in the network recognized their exceptional performance.

Having three subgroups, with one of them containing only three employees, a statistical comparison of the consumer collaboration subgroups with respect to performance was not possible. However, one aspect of the results was immediately apparent: the consumer subgroup 1 {J, O, Q} (employees who sought

Table 5. Mean Performance and Personality Ratings for the Producer and Consumer Subgroups of the Collaboration Network.

	Producers		Consumers		
	Subgroup 1 {H, A, E, K, N, C, P}	Subgroup 2 {B, D, F, G, I, J, M, O, Q}	Subgroup 1 {J, O, Q}	Subgroup 2 {A, B, E, F, G, N}	Subgroup 3 {C, D, H, I, K, M, P}
Team performance	6.29	5.22	5.00	5.83	5.86
Individual performance	6.57	5.33	4.67	6.17	6.14
Overall performance	6.71	5.00	5.33	5.83	5.86
Openness	5.14	5.61	5.17	5.67	5.29
Agreeableness	3.79	3.72	3.50	3.50	4.07
Conscientiousness	4.21	3.94	4.00	4.33	3.86
Emotional	4.93	5.11	4.67	5.75	4.57
Extroversion	3.93	5.17	5.17	5.08	4.00

collaboration with just about everyone) had the lowest mean ratings for team, individual, and overall performance. This suggests these individuals did recognize the perception of their performance and desired collaboration to improve their standing.

Finally, with respect to the research question #4 pertaining to the personality measures, the means for the two producer subgroups were not judged to be significantly different for any of the big-five personality dimensions. Again, this is largely attributable to the small sample sizes. Nevertheless, the disparity for the extroversion dimension is quite large, with the mean for the highly sought-after subgroup more than one full rating point lower than that of the other subgroup. By contrast, when considering the consumer subgroups, the small cluster of heavy collaboration seekers {J, O, Q} had the highest mean extroversion rating, whereas the consumer subgroup 3 (the subgroup that sought collaboration the least) had the lowest mean extroversion.

CONCLUSION

Blockmodeling methods can serve HRM scholars in several ways. Specifically, blockmodels can (1) simplify and reduce complex structural data, (2) uncover networks structures and subgroups, and (3) identify emergent roles for analysis. The examples provided throughout this work are intended to demonstrate the various approaches HRM scholars can take in utilizing blockmodeling methods. In short, blockmodeling methods group structurally similar individuals into groups called positions which are associated with blocks of ties between positions. These can be coupled to roles (sets of expectations) for members of specific positions. Although the basic objective is to discern the fundamental underlying structure of a network, we regard blockmodeling as more fruitful when coupled strongly to the exploration of substantive issues so that the resulting blockmodel will be more useful. Indeed, substance can be used to specify blockmodel forms when researchers have the knowledge for doing this. Even though there are circumstances where an exploratory approach is the only realistic option, we believe there will be many more deductive uses of blockmodeling (Doreian et al., 2005) in future research.

Applications of social network analysis abound in the organizational sciences literature, but practical implementations of blockmodeling are relatively scarce. Our goal here was to introduce the topic of blockmodeling, provide a brief review of its history, and demonstrate blockmodeling using a real empirical example. We hope this can help overcome one of the major impediments to blockmodeling in the organizational sciences in general and HRM: namely, a seeming lack of familiarity with the topic. Nevertheless, other obstacles may remain that we hope can be overcome. For example, part of the reluctance to employ blockmodeling tools might stem from its perceived relationship to cluster analysis, which can be perceived as *ad hoc* in nature and generally not conducive to hypothesis testing. Indeed, blockmodeling has often been used in this fashion. However, in its origins, blockmodeling was informed by substantive concerns and recent applications in the social network literature have stressed substance in the formulation of blockmodeling problems and testing the resulting blockmodels with data.

Blockmodeling is not a "cookie cutter" approach to understanding the fundamental structure of social networks. Constructing blockmodels of networks requires thought about how to view a network, the types of equivalence necessary for an analysis, and the specification of the criterion function. We urge HRM scholars to delve into the rich body of work in blockmodeling methods to pair with a strong theoretical framework and find appropriate ways for addressing their specific research questions. Our experience is that when blockmodeling is applied in new domains, new issues are raised that require careful attention. Our empirical example was selected to convey some of the key decision points of the blockmodeling process, along with a focus on substantive issues within HRM research. Although blockmodeling can be very useful as an exploratory tool for describing network structure, a much more valuable use of blockmodeling stems from formulating substantive blockmodels and testing them with empirical data. Both exploratory (inductive) and confirmatory (deductive where a blockmodel has been specified in part or completely) blockmodeling can have greater importance in HRM studies.

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