Understanding the structures, antecedents and outcomes of organisational learning and knowledge transfer: a multi-theoretical and multilevel network analysis

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Abstract: The goal of this study was to develop a multi-theoretical and multilevel model to study organisational learning and knowledge transfer. We employed a social network approach to theorise and empirically test the structures, antecedents and outcomes of intra-organisational information retrieval and allocation. Data were collected from 110 individuals across nine work teams, and analysed using Exponential Random Graph Modelling (ERGM) technique. The results found a multiplexity and reciprocity of team members' information retrieval and allocation, as well as a predominant centralised structure of information retrieval. Furthermore, there was a tendency for members to retrieve and allocate information across job positions. Finally, members were more satisfied with their team work when proactively retrieving information from others than when receiving unsolicited information allocated from others. This study has important theoretical and practical implications for understanding and managing organisational knowledge and learning networks.

Keywords: organisational learning; knowledge transfer; information retrieval; information allocation; ERGM analysis.

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1 Introduction

In the emerging knowledge economy, individual knowledge has become a 'competitive advantage' for organisations (Badaracco, 1991; Davenport and Prusak, 1998). However, the specialisation and distribution of knowledge among organisational members create barriers for them to effectively identify, retrieve and transfer knowledge in need (Hollingshead, 1998a). Brown and Duguid (2000, p.150) noted that organisational knowledge as a competitive advantage 'could not always be found, and when it was, it could not be moved'. In response to such challenges, increasing research attention has been paid to using a social network perspective to study how knowledge is learned and transferred in organisational knowledge networks (Kilduff and Tsai, 2003; Monge and Contractor, 2003; Cross and Borgatti, 2004).

While there is a wealth of literature on organisational learning and knowledge transfer (cf. Huber, 1991; Miner and Mezias, 1996; Argote and Ingram, 2000; Argote et al., 2000), research on learning and knowledge networks is limited. Prior research has examined the effects of network centrality (Tsai, 2001) and strengths of network ties (Krackhardt, 1992; Hansen, 1999; Levin and Cross, 2004) on organisational knowledge transfer. Other studies focus on inter-unit knowledge exchange networks (Hansen, 2002; Tsai, 2002), information seeking through social networks (Cross and Sproull, 2004), roles of human resource managers in knowledge networks (Zupan and Kaše, 2007) and coevolution of communication and knowledge networks (Palazzolo et al., 2006). However, scholars share their concerns that many network studies are mainly method-driven and atheoretical (Granovetter, 1979; Salancik, 1995), and lack empirical validation (Škerlavaj and Dimovski, 2007). To address these concerns and to advance our understanding of organisational learning and knowledge transfer, this study seeks to theorise and empirically test a network model of the structures, antecedents and outcomes of organisational knowledge and learning networks.

As two crucial constructs of organisational learning are knowledge acquisition and information distribution (Huber, 1991), our study focuses on two integral processes in building knowledge and learning networks: *information retrieval* and *information allocation*. Information retrieval is defined as seeking and receiving needed information in a given knowledge domain, and information allocation refers to the process in which new information is shared with and communicated to others (Wegner, 1995; Hollingshead, 1998b). Information retrieval is related to learning and acquiring 'what others know', whereas information allocation is associated with sharing and distributing 'what I know'. In this study, we develop a Multi-Theoretical and Multilevel (MTML) model (Monge and Contractor, 2003) to examine the following:

1 The emerging structures of team members' information retrieval and allocation networks.

2 The effects of perceived value of knowledge sharing and job homophily on organisational learning and knowledge transfer.

3 The effects of information reception on members' satisfaction with teamwork.

This paper begins with an introduction to the MTML framework and development of the structural models. The subsequent sections present the antecedent and outcome models of knowledge and learning networks. The remainder of the paper reports research methods, results and discussions of this study.

2 Structures of knowledge and learning networks

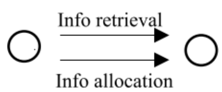
Knowledge networks emerge as organisational members use flexible and dynamic communication relationships to retrieve and transfer knowledge. To better understand how individuals create, maintain and reconstitute their relational ties with others in the knowledge network, Monge and Contractor (2003) proposed an MTML framework. This approach is multi-theoretical in that it synthesises a collective of social theories and articulates the fundamental network mechanisms embedded in each theory. Then these theoretical mechanisms are used in conjunction with each other to explain specific structures and properties of a network. The multi-theoretical approach is 'to help compare and integrate diverse theories and to increase the explanatory power of research efforts' (Monge and Contractor, 2003, p.xii). Furthermore, the MTML framework examines network structures that emerge at all levels within a specific network, e.g. individual, dyadic, triadic, group and global (the entire network) level. This multilevel framework advances traditional social science research that tends to focus on a single level of analysis, and provides a more comprehensive analytic context for network research.[1]

Previous research has demonstrated the theoretical and empirical viability in using the MTML approach to study inter-organisational communication networks (Contractor et al., 2006), intra-organisational learning networks (Škerlavaj and Dimovski, 2007) and team-level information retrieval networks (Su, 2008). In the present study, we seek to apply the MTML framework to examine the structures, antecedents and outcomes of organisational learning and knowledge transfer. First, we propose four structural models based on transactive memory theory. Transactive memory theory provides important network mechanisms to explain the basic structures of team members' information retrieval and allocation relationships (Monge and Contractor, 2003; Palazzolo, 2005). Second, we utilise public goods theory and homophily theory to understand how individual attributes could influence their information retrieval and allocation behaviours in the knowledge network. Finally, based on extant research on organisational job satisfaction, we propose an outcome model to examine the effects of team members' knowledge retrieval and transfer on their satisfaction with teamwork.

The goal of this study is to develop an integrated and comprehensive theoretical model in which the hypothesised network structures are driven and explained by a multitude of theoretical mechanisms. Each of these theories has previously been well established and applied to explain organisational knowledge sharing and transfer. However, what remains unknown is whether and how these theoretical mechanisms would work together when they are integrated into the same analytical framework. For example, will team members' information retrieval be predominantly driven by transactive memory development or job homophily? Which theoretical mechanism would provide greater explanatory power relative to other theoretical explanations? Our study seeks to contribute to current literature by addressing these questions. Furthermore, our proposed theoretical models encompass different levels of team members' information retrieval and allocation networks, including individual attributes, dyadic multiplexity and reciprocity, and global in-star structures (explained in detail in the analysis section). This multilevel approach helps bridge the limitations of previous organisational research that tends to focus on a single level of analysis, typically the individual or dyad (Monge and Contractor, 2003).

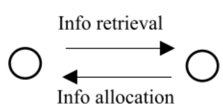
2.1 Transactive memory theory

Transactive memory theory (cf. Wegner et al., 1985; Wegner, 1987; Wegner et al., 1991) explains how a group of individuals store, retrieve and share information to effectively manage their collective and distributed knowledge. In a transactive memory system, work groups distribute information across individual members based on their specialised areas of expertise and responsibility (Hollingshead, 2000). When group members need knowledge outside their areas of expertise, they would retrieve relevant information from someone whom they perceive to be knowledgeable or responsible for that particular knowledge domain (Hollingshead, 1998b). Likewise, when they come across information in that knowledge domain, as they do not possess adequate knowledge to properly handle and utilise such information, they would allocate the information to those from whom they retrieve information in the same knowledge domain. In this way, information in the relevant knowledge domain is properly kept and stored with member(s) who hold expertise and responsibility for that knowledge domain, and others can effectively identify and retrieve such information in the future. Therefore, we propose the following multiplexity structure (i.e. one type of interpersonal relationship is accompanied by another type of interpersonal relationship in the same direction) regarding team members' information retrieval and allocation.



H1: One member tends to retrieve information from another member to whom one allocates unsolicited information in the same knowledge domain.

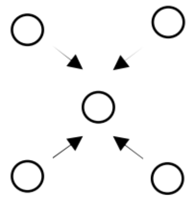
A fundamental premise of transactive memory theory is that members develop a directory of 'who knows what' or 'who is responsible for what' to determine where to go for information in a particular knowledge domain (Wegner et al., 1991). A parallel process that has been overlooked in prior transactive memory research is that knowledge providers may also develop a directory of 'who needs what information' to determine with whom to share information in a specific knowledge domain. When receiving information requests, knowledge providers may consider such requests as indicators of information seekers' lack of knowledge and needs for information. Thus, they are likely to allocate unsolicited information to information seekers in the relevant knowledge domain. Therefore, we extend transactive memory theory to predict a reciprocal structure (i.e. one type of interpersonal relationship is accompanied by another type of relationship in the opposite direction) of team members' information retrieval and allocation.



H2: One member's information retrieval from another member tends to be reciprocated by the other member's allocation of unsolicited information to oneself in the same knowledge domain.

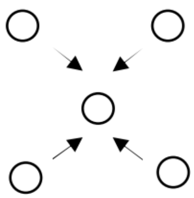
The above hypotheses focus on the dyadic relationship within the knowledge and learning network. At the global level (i.e. involving multiple members in the same team), we predict a centralised structure of team members' information retrieval and allocation. In a well-established transactive memory system, knowledge in a particular domain is narrowly distributed and highly concentrated on one or a few individuals. In this way, there is a minimal level of information redundancy and a maximal volume of collective expertise across all knowledge domains (Moreland, 1999). Thus in a particular knowledge domain, only one or a few members would emerge as the 'star' of the knowledge and learning network. Thus we propose the following centralised network structures of team members' information retrieval and allocation at the team level. A network is centralised if a few members have considerably more relational ties than others in the network (Monge and Contractor, 2003).

Info retrieval



H3a: Team members tend to retrieve information from one or a small number of others in a particular knowledge domain.

Info allocation



H3b: Team members tend to allocate unsolicited information to one or a small number of others in a particular knowledge domain.

3 Antecedents of knowledge and learning networks

The previous structural models applied transactive memory theory to examine the structural properties of team members' information retrieval and allocation networks. However, according to Monge and Contractor's (2003) MTML framework, a single theory or theoretical mechanism is usually inadequate to provide a comprehensive explanation of organisational communication and knowledge networks. For example, an important question not addressed in the structural models is: What are the antecedent factors that influence the emerging structures of knowledge and learning networks? Therefore, in addition to transactive memory theory, it is important to utilise complementary theoretical mechanisms to further understand how individual attributes affect their tendencies to create network ties for information retrieval and allocation. In the following section, we focus on two antecedents to team members' information retrieval and allocation:

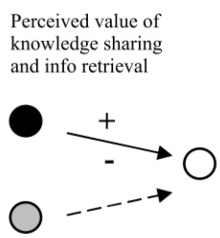
1 individual's perception of the value of knowledge sharing and

2 team members' homophily in job positions.

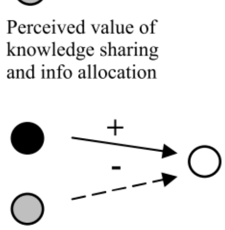
3.1 Perceived value of organisational knowledge sharing

A group of scholars has suggested public goods theory to complement transactive memory theory in studying interactive communication systems in organisations (Fulk et al., 1996; Hollingshead et al., 2002; Monge and Contractor, 2003). Originally developed to examine collectively shared and publicly accessible physical goods such as parks and libraries (Samuelson, 1954; Hardin, 1982; Marwell and Oliver, 1993), public goods theory has been applied to conceptualise and analyse organisational knowledge as a form of public goods (Connolly and Thorn, 1990; Monge et al., 1998; Fulk et al., 2004). It is argued that task-related knowledge possessed and shared by organisational members also demonstrates the 'non-excludable' and 'non-rivalrous' characteristics of a traditional public good (Yuan et al., 2005). In general, no individual employee is excluded or banned from seeking or sharing task-related knowledge to accomplish their job tasks. On the other hand, one member's information retrieval from an expert would not eliminate or reduce the quality and access of such expertise to other members. Therefore, the collective use and transfer of organisational knowledge possessed by each individual can be and should be examined from the public goods perspective.

In principle, public goods theory seeks to explain how individual members are induced to use and contribute to public goods (Marwell and Oliver, 1993). When the theory is applied to examine organisational knowledge as a public good, it is suggested that people's tendency to use and contribute to such knowledge good is influenced by their perceptions of the value of organisational knowledge sharing (Monge et al., 1998). When individuals perceive greater value of knowledge sharing within the organisation, they are more likely to contribute to the collective knowledge good by sharing 'what they know' and allocate information to those in need. To compensate for their contributions to the public knowledge good, people are also likely to utilise and leverage such knowledge good by retrieving 'what they need' from other members. Thus we propose the following hypotheses.



H4a: Team members who perceive greater value of knowledge sharing are more likely to retrieve information from other members than those who perceive lower value of knowledge sharing.

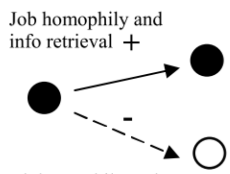


H4b: Team members who perceive greater value of knowledge sharing are more likely to allocate unsolicited information to other members than those who perceive lower value of knowledge sharing.

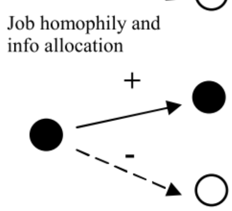
3.2 Effects of job homophily on knowledge and learning networks

The emergence of organisational knowledge networks could also be influenced by the homophily of individual attributes (Monge and Contractor, 2003). Theory of homophily describes a principle that 'a contact between similar people occurs at a higher rate than among dissimilar people', a phenomenon known as 'birds of a feather flock together' (McPherson et al., 2001, p.416). The rationale for the homophily effects is that people with similar attributes are often exposed to comparable values, similar constraints, socialisation and organisational experiences (Burt, 1987), and such similarities can enhance mutual attractions and increase the frequency and quality of interactions (Barsness et al., 2005). In the context of organisational learning and knowledge transfer, research has found that organisational members tend to seek information from members of the same gender due to shared perspectives and communication styles (Cross et al., 2001). Interestingly, Ibarra (1992) found that women were likely to go to male colleagues for task-related information, but to female colleagues for social support.

Employees' homophily in job positions can also influence interpersonal knowledge transfer (Darr and Kurtzberg, 2000). As Rogers and Bhowmik (1970) asserted that individuals might be more effective at communicating with members from similar professional backgrounds and with similar task assignments. Other research suggested that individuals would have a greater level of comfort, shared understanding and trust with their peers than with supervisors (Brass, 1995; Carley, 2002), which could facilitate effective knowledge retrieval and transfer (Cross and Borgatti, 2004; Levin and Cross, 2004). Thus we propose that organisational members are more likely to engage in information retrieval and allocation with others who are homophilous in job position.



H5a: Team members are more likely to retrieve information from others in the same job position than from those in a different job position.



H5b: Team members are more likely to allocate unsolicited information to others in the same job position than to those in a different job position.

4 Outcomes of knowledge and learning networks

So far, our theoretical models have examined the structures and antecedents of organisational knowledge and learning networks. In the following outcome model, we focus on the effects of information reception on individual's satisfaction with teamwork. Locke (1976) provided a summary of previous research on the nature and causes of organisational members' job satisfaction, in which he suggested that employees' job satisfaction was influenced by their reception of critical information such as task activities, working conditions and management practices. A later longitudinal study found that group members' job satisfaction was positively affected by the quality of information acquired from group members (Flanagin et al., 2004). In today's organisations, an increasing number of tasks must be carried out and accomplished through teamwork, which requires a smooth transfer of individually possessed information that is essential for interdependent task completion (Faraj and Sproull, 2000; Hollingshead, 2001). Therefore, we argue that those members who receive information from their team members, either through proactive retrieval or passive reception of unsolicited information allocated from others, are likely to have a greater level of satisfaction with the teamwork.

Info retrieval and
job satisfaction

H6a: Team members who retrieve information from other members tend to have a greater level of satisfaction with teamwork than those who do not.

Info allocation and
job satisfaction

H6b: Team members who receive unsolicited information allocated from other members tend to have a greater level of satisfaction with teamwork than those who do not.

5 Method and analysis

5.1 Sample and procedure

To test our hypotheses, we collected network data from nine teams working in two multinational consulting firms in Western Europe. Each of these nine teams worked in a local project site of their parent firm. The teams had been working with their clients for at least half a year at the time of data collection. Teams ranged in size from 8 to 20 members with a total of 110 participants in our study. On average, members were 32 years old (*SD* = 3.96) and had worked in the firm for 2.76 years (*SD* = 2.11). Table 1 demonstrates the basic demographic and work-related information of these teams.

Table 1 Team information (response rate = 100%)

Team ID	*Size*	*Company affiliation*	*Number of knowledge domains*	*Mean info retrieval*[a]	*Mea info allocation*	*Age*		*Tenure*	
						Mean	*SD*	*Mean*	*SD*
1	20	Consulting Firm A	6	0.38	0.53	33.25	7.62	2.75	4.65
2	12	Consulting Firm A	6	0.20	0.46	34.91	7.69	5.36	5.12
3	13	Consulting Firm A	7	0.23	0.52	33.46	4.03	3.7	3.19
4	9	Consulting Firm A	6	0.38	0.44	33.33	3.28	2.42	1.07
5	12	Consulting Firm A	7	0.19	0.48	30.67	2.94	1.58	0.63
6	12	Consulting Firm A	5	0.44	0.60	29.08	2.31	2.42	1.17
7	8	Consulting Firm A	8	0.16	0.47	30	2.2	2.38	1.14
8	11	Consulting Firm A	7	0.37	0.63	30.1	4.4	1.73	1.18
9	13	Consulting Firm B	4	0.31	0.58	29.85	1.41	2.51	1.35
Mean	12	–	6	0.30	0.52	31.62	3.96	2.76	2.11
Total	110	–	56	–	–	–	–	–	–

Notes: [a]The mean information retrieval and allocation relationship are represented by the density of information retrieval and allocation networks. Network density is defined as the total number of ties divided by the total number of possible ties in a given network (Borgatti et al., 1999), which measures the average occurrence of a relational tie in a network. The range is from 0 to 1.

Data were collected through a web-based network survey titled the *Knowledge Asset Mapping Exercise* (KAME). Initially, leaders in each team were interviewed to identify several knowledge domains that were essential for their task completion. There were 56 knowledge domains across these nine teams, ranging from four to eight in each team. Based on these interview results, a KAME was customised for each team before participants were granted private access to complete it online.

5.2 Measures

The two key variables in our analysis are the information retrieval and allocation networks. In the KAME, participants were asked to report how often they *retrieved information from* and *allocated unsolicited information to* every other member in each knowledge domain. The responses were on a 5-point scale ranging from *never* to *very often*. Participants were also asked to answer a 4-item scale regarding their perceptions of the value of knowledge sharing. In the present study, we operationalise this variable as individual's general perception of the importance in knowledge sharing, as well as anticipated organisational and individual benefits from knowledge sharing. The responses to each item were on a 5-point scale ranging from *strongly disagree* to *strongly agree*. Team members' satisfaction with team work was measured by a 3-item scale. The responses to each item were on a 5-point scale ranging from *very dissatisfied* to *very satisfied*. Finally, team members identified their job positions (organisational ranks) in the organisation.

The appendix provides a detailed description of the KAME questions used for this study.

5.3 Analysis

To test our hypotheses, we used a social network analysis technique, ERGM (Exponential Random Graph Modelling), also known as p^* analysis (Frank and Strauss, 1986; Wasserman and Pattison, 1996; Robins and Pattison, 2005). ERGM analysis appropriately estimates the degree to which the theoretically hypothesised substructures are likely to occur (Robins et al., 2007). In other words, ERGM analysis tests the statistical likelihood for our hypothesised network structure to be observed in the data we collected. As our hypotheses involved multiple relationships (e.g. information retrieval and allocation) and individual attributes (e.g. job position and satisfaction with teamwork), we analysed a multivariate and multi-attribute ERGM model (Pattison and Wasserman, 1999) in XPNet, a computer program designed specifically for analysing social networks with multiple relationships and attributes (Wang et al., 2006).

As our data were based on organisational work teams, we fitted a single ERGM model for each team across all knowledge domains reported by the team.[2] This model includes all hypothesised effects in our theoretical models: structural (H1–H3), antecedent (H4–H5) and outcome (H6) effects. By fitting all hypothesised effects within one analytical framework, we have greater confidence in determining the effects of a particular network substructure, while the effects of all other substructures are accounted for in the same model (Robins et al., 2007). In this way, we are able to estimate the effects of all hypothesised network substructures simultaneously, rather than separately.

To test the magnitude and significance level of hypothesised effects, we estimated a series of parameters in the ERGM model, each of which corresponded to a specific network substructure proposed in our hypotheses. A positive and significant estimate for a particular parameter indicates that networks with a large number of substructures corresponding to the parameter are statistically more likely to occur than by a random chance (Wasserman and Robins, 2005). In general, there is a monotonic though non-linear relationship between the value of a parameter estimate and the expected number of corresponding substructures in a network.

To test *H1*, we estimated the *multiplexity* parameter of information retrieval and allocation relations. The multiplexity parameter tests the tendency for two or more relational ties to co-occur in the same direction between the same pair of members in a network. To test *H2*, we estimated the *reciprocity* parameter of information retrieval and allocation relationships in the network. This parameter tests the degree to which member *i*'s information retrieval from member *j* is reciprocated by *j*'s information allocation to *i*. To test *H3a* and *H3b*, we estimated the *in-k-star* parameter of information retrieval and allocation, respectively. This parameter assesses the degree to which one member has multiple incoming relational ties from other members in the network, which is an index of network centralisation (Scott, 2000; Palazzolo, 2005). To test *H4a* and *H4b*, we estimated the *choice* parameter of information retrieval and allocation, respectively, while taking into consideration team members' perceptions of the value of knowledge sharing. The choice parameter itself estimates a member's tendency to create a relational tie with others in the network. When individual attributes are taken into consideration, the choice parameter estimates whether members with greater levels of such attributes are more likely to create a relational tie with others than those with lower levels of such attributes. To test *H5a* and *H5b*, we estimated the *choice* parameter of information retrieval and allocation, respectively, based on the similarity of two members' job positions. Finally, to test *H6a* and *H6b*, we estimated the *sender effect* of information retrieval and *receiver effect* of information allocation while considering the information recipient's satisfaction with their teamwork.

In sum, to test our hypotheses, we estimated a single ERGM model for each team that included the following hypothesised network substructures:

1 multiplexity of information retrieval and allocation

2 reciprocity of information retrieval and allocation

3 in-k-star information retrieval

4 in-k-star information allocation

5 choice of information retrieval based on individual's perception of the value of knowledge sharing

6 choice of information allocation based on individual's perception of the value of knowledge sharing

7 choice of information retrieval based on job homophily

8 choice of information allocation based on job homophily

9 satisfaction based on information retrieval

10 satisfaction based on reception of information allocated from others.

6 Results

6.1 *Results for structural models*

The EGRM analysis results for structural models (*H1–H3*) are presented in Table 2. The value of a parameter estimate represents the likelihood for the corresponding hypothesised substructure to be observed in the data we collected. Again, it is monotonically related to the expected number of corresponding substructures to occur in observed networks. *H1* posits a multiplexity of team members' information retrieval and allocation. As demonstrated in Table 2, this hypothesis is supported (indicated by significantly positive parameter estimates) in all teams but Team 9. These results suggest that there is a predominant network structure in most teams that members are likely to retrieve information from those to whom they allocate unsolicited information in the same knowledge domain.

Table 2 ERGM analysis results[a] for structural models (H1–H3)

Team ID	*Multiplexity of info retrieval and allocation (H1)*	*Info retrieval reciprocated by info allocation (H2)*	*Centralisation of info retrieval (H3a)*	*Centralisation of info allocation (H3b)*
1	1.86 (0.12)*	0.08 (0.14)	2.06 (0.17)*	–2.76 (0.05)*
2	1.37 (0.23)*	1.15 (0.24)*	1.41 (0.16)*	0.51 (0.19)*
3	2.35 (0.22)*	0.88 (0.24)*	1.50 (0.14)*	0.24 (0.18)
4	1.79 (0.31)*	0.13 (0.30)	1.81 (0.18)*	–0.26 (0.30)
5	1.99 (0.25)*	1.85 (0.26)*	1.37 (0.15)*	–0.21 (0.22)
6	1.94 (0.27)*	0.90 (0.27)*	1.71 (0.23)*	–1.52 (1.97)
7	2.34 (0.38)*	1.67 (0.39)*	1.26 (0.21)*	0.42 (0.22)
8	0.84 (0.25)*	1.16 (0.23)*	2.11 (0.15)*	–0.01 (0.35)
9	–0.37 (0.27)	0.40 (0.19)*	1.81 (0.17)*	0.73 (0.30)*

Notes: [a]We report the ERGM analysis results for each of the nine work teams. In each cell of Tables 2–4, the value of parameter estimation is reported, with the standard error included within brackets. The statistical significance of a parameter estimate is flagged by*, which indicates that the estimate value is at least twice the standard error.

H2 hypothesises that an information seeker's information retrieval is likely to be reciprocated by the information provider's allocation of unsolicited information in the same knowledge domain. This hypothesis is supported in all teams but Teams 1 and 4. The results suggest that most teams in our study have established an extended transactive memory system that is rarely studied in prior research. In such a system, not only information seekers are actively retrieving knowledge from others, but also information providers are allocating unsolicited information to information seekers in the relevant knowledge domain.

H3a and *H3b* predict a centralised network structure of information retrieval and allocation. The parameter estimate for *H3a* is significantly positive in all teams, which supports this hypothesis. This finding demonstrates a unanimously centralised and concentrated knowledge acquisition structure in all teams.[3] However, *H3b* is supported in two teams only. The results imply that while team members are likely to concentrate their information retrieval from only one or a few members, their information sharing and allocation relationships are uniformly distributed within the team.

6.2 Results for antecedent models

Table 3 reports the ERGM analysis results for antecedent models (*H4* and *H5*). *H4a* and *H4b* posit that team members' information retrieval and allocation would be influenced by their perceptions of the value of knowledge sharing. *H4a* is supported in only one team (Team 7), which means team members' perceptions of the value of knowledge sharing did not actually increase their tendencies to retrieve information from other members. In contrast, *H4b* is supported in five teams, more than half of all teams we studied. Such results imply that members' perceived value of knowledge sharing would exert a stronger influence on their information allocation than on their information retrieval.

Table 3 ERGM analysis results for antecedent models (H4–H5)

Team ID	*Info retrieval driven by perceived value of knowledge sharing (H4a)*	*Info allocation driven by perceived value of knowledge sharing (H4b)*	*Info retrieval driven by job homophily (H5a)*	*Info allocation driven by job homophily (H5b)*
1	–0.82 (0.10)*	0.92 (0.10)*	0.59 (0.29)*	1.32 (0.31)*
2	0.16 (0.23)	1.39 (0.25)*	0.33 (0.34)	–0.80 (0.50)
3	–0.51 (0.25)*	0.81 (0.23)*	–0.12 (0.24)	0.64 (0.24)*
4	–0.17 (0.19)	–0.19 (0.18)	0.06 (0.40)	0.34 (0.40)
5	0.26 (0.16)	0.93 (0.17)*	0.33 (0.34)	–0.95 (0.44)*
6	–0.11 (0.22)	–0.19 (0.20)	–0.11 (0.24)	–0.03 (0.32)
7	1.16 (0.34)*	–0.09 (0.33)	0.47 (0.50)	–0.81 (0.58)
8	–0.15 (0.17)	–0.20 (0.14)	–0.05 (0.31)	–0.11 (0.29)
9	0.01 (0.16)	0.62 (0.14)*	–0.71 (0.23)*	–0.44 (0.25)

H5a and *H5b* posit that team members' information retrieval and allocation would be influenced by their homophily in job positions. However, neither hypothesis is supported in more than half of all participating teams. There is no strong evidence that team members tend to engage in peer-to-peer knowledge retrieval and allocation. Instead, members are more likely to retrieve and allocate information across organisational ranks and job positions.

6.3 Results for outcome models

Finally, the outcome models predict that team members would have a greater level of satisfaction with their teamwork when they retrieve information from others (*H6a*), and receive unsolicited information allocated from others (*H6b*). As demonstrated in Table 4, *H6a* is supported in six out of nine teams in our study, whereas *H6b* is not supported at all. Such contrasting results suggest that team members are more satisfied with their teamwork when they proactively retrieve information from others than when they passively receive unsolicited information allocated from their colleagues.

Table 4 ERGM analysis results for outcome models (H6)

Team ID	*Satisfaction with teamwork when retrieving info from others (H6a)*	*Satisfaction with teamwork when receiving info allocated from others (H6b)*
1	0.21 (0.06)*	–0.01 (0.02)
2	0.04 (0.08)	–0.14 (0.06)*
3	0.37 (0.11)*	–0.11 (0.08)
4	0.29 (0.13)*	0.09 (0.13)
5	0.64 (0.12)*	0.12 (0.11)
6	0.75 (0.13)*	0.20 (0.14)
7	0.25 (0.32)	–0.16 (0.23)
8	0.07 (0.12)	–0.07 (0.10)
9	0.81 (0.18)*	–0.26 (0.15)

7 Discussion

The goal of this study was to develop an MTML network model of organisational learning and knowledge transfer. Specifically, we focused on the structures, antecedents and outcomes of team members' information retrieval and allocation. By analysing empirical network data collected from multiple work teams, we found support to two predominant substructures in their knowledge and learning networks: the multiplexity of information retrieval and allocation, and the centralisation of information retrieval. Both structures conform to the principle assertions of transactive memory theory (Wegner, 1987). Thus our study provided additional empirical support to the fundamental network structures of information retrieval and allocation identified in transactive memory literature.

More importantly, our study contributes to transactive memory research by discovering an advanced development of transactive memory system. Analysis results of *H2* demonstrated that knowledge providers did reciprocate information seekers' retrieval requests with allocation of unsolicited information in the same knowledge domain. Such finding extends previous transactive memory research, which mainly focuses on a one-way investigation of information retrieval without studying how knowledge providers respond and follow up with information requests (Hollingshead, 1998b; Palazzolo, 2005). An important implication of this finding is that, while information seekers retrieve information based on 'who knows what' in the transactive memory system, knowledge providers may also develop a directory of 'who needs what' to determine what and with whom information should be shared (Hollingshead et al., 2007). In this way, these knowledge providers play a more important role than simply providing information in the transactive memory system. They are also fulfilling their responsibilities as educators or mentors in the knowledge and learning network (Huang, 2009).

7.1 Centralisation vs. decentralisation of knowledge and learning networks

Our study found a unanimous centralised structure of information retrieval in all teams, which concurred with the findings from a previous study on information retrieval in transactive memory systems (Palazzolo, 2005). The concentration of information retrieval suggests that organisational knowledge might be narrowly distributed in our participating teams, and only one or a few members would emerge as central knowledge sources in the organisational learning networks. Although such a star pattern of knowledge retrieval may provide information seekers an efficient conduit for information seeking, it may create overwhelming burdens on knowledge providers (the 'stars'), which may potentially reduce the quality and accuracy of their information provision and impair their willingness to engage in knowledge sharing and transfer.

While there is a predominant centralised information retrieval structure in our participating teams, the pattern of their information allocation is decentralised and uniformly distributed. In other words, team members tend to allocate and distribute information to many others rather than just one or a few. Although such a decentralised information allocation structure does not strictly comply with the transactive memory theoretical argument, it does not necessarily carry a negative impact on knowledge and learning networks. Previous studies have found that decentralised network structures could provide more opportunities for task-related communication and information exchange (Albrecht and Ropp, 1984), augment group performance by fostering knowledge sharing (Rulke and Galaskiewicz, 2000) and improve team creativity (Leenders et al., 2003). Especially in the consulting industry, as the processes and outputs are knowledge intensive and information driven, a decentralised information allocation structure may facilitate an extensive distribution of critical information, and help cultivate a cohesive and collaborative working environment.

7.2 Interplay between individual attributes and information sharing

Our study provides complementary findings to public goods research on why organisational members would be induced to contribute to public knowledge goods, also known as organisational information commons (Fulk et al., 2004; Yuan et al., 2005). We found that while an individual's perception of the value of knowledge sharing would increase team members' propensity to contribute to the information commons by allocating information to others, such perceptions would not increase their tendency to benefit from the public knowledge good by retrieving information from others. Therefore, even though information retrieval and allocation are two integrated components of the knowledge and learning network, individuals are likely to be driven by distinct motivating factors to utilise as compared to contribute to organisational information commons. Our study reiterates the importance in a more careful examination of the effects of cognitive motivation on realising potential benefits of information seeking and sharing networks (Anderson, 2008).

Although the present research did not find a strong support for the homophily effects on team members' information retrieval and allocation, we were encouraged by the fact that our participants were acquiring and distributing information across their job positions. One of the defining characteristics of emerging network organisations (DeSanctis and Monge, 1999) is a flexible and permeable boundary of information sharing and coordination. A recent study showed that interdisciplinary heterogeneity at workplaces would improve decision-making processes for greater innovations (Henneke and Luthje, 2007). We believe that while peer-to-peer learning and knowledge transfer are important for task completion, vertical and cross-boundary information sharing and retrieval are essential to sustainable growth and innovation of the organisation.

Finally, we found that team members were more satisfied with their teamwork when proactively retrieving information from other members than receiving unsolicited information allocated from others. As a matter of fact, since many of the parameter estimates were negative for *H6b* (although not statistically significant, see Table 4), receiving unsolicited information might even decrease members' satisfaction with their teamwork. This finding corresponds to an increasing concern of the negative impact of an overwhelming volume of information reception, dubbed as *information tsunami* (Bruck, 2002) or *information overload* (Huber, 1991). Studies have claimed that information overload could lead to ineffective interpretation of information (Huber, 1991), and a high cost of time, money and energy for information processing and management (Feldman and Sherman, 2001). Our study adds to this line of research by suggesting that information overload may negatively affect employees' satisfaction with their teamwork as well.

7.3 Micro-foundations of organisational learning and knowledge networks

Traditional organisational learning literature conceptualises and operationalises the learning process and outcome primarily at the collective (group or organisational) level (Huber, 1991; Kogut and Zander, 1996; Miner and Mezias, 1996). However, we concur with Felin and Foss' (2005) call for more research attention to the micro-foundation of organisational routines and capabilities, especially the relationship of individual action and attributes with collective structures and outcome. After all, individuals 'provide the nested antecedent to numerous collective phenomena and thus deserve careful theoretical and empirical consideration in our theorising' (Felin and Foss, 2005, p.452). Their visions are shared by Coleman (1990) who argues for the critical importance in studying individuals as the central and fundamental actors in social theory development.

In our study, while the structural models focus on the collective property (dyadic and network structures) of organisational learning and knowledge transfer, our antecedent and outcome models concentrate on the mutual effects between individual attributes and their knowledge networks. Thus we have proposed an integrated network model that examines not only the network structures at the collective level, but more importantly the micro-foundations of organisational learning and knowledge networks, i.e. how the structures of organisational learning networks are created and emerge from individual information retrieval and allocation behaviours, and how individual attributes are affected by the subsequent interaction between individuals and the collective. For example, we found a unanimous centralised network structure of information retrieval in all teams, which was rendered by individual members' choice of seeking information from only a few rather than many others in the knowledge network. On the other hand, we found that team members' satisfaction levels were related to their active information retrieval behaviours. Thus the individual-level outcome would in return help explain the emergence of such a centralised information retrieval structure.

In sum, our study has two unique contributions to current research on knowledge and learning networks. First, we employ a social network perspective to develop theory-driven models of team members' information retrieval and allocation. Our study showcases the importance and viability in utilising an MTML framework and advanced social network analysis tools to examine the richness and dynamics of organisational knowledge networks. Second, above and beyond the traditional focus on network structures, the present research also studies the antecedents and outcomes of knowledge networks. The structural, antecedent and outcome models complement each other in providing a comprehensive theoretical framework to enrich our understanding of organisational learning and knowledge transfer, both at the individual and collective level.

7.4 Practical implications

Our study has important and useful implications for managerial practices. First, we suggest that organisations should not indiscriminately embrace a centralised structure or reject a decentralised structure of knowledge and learning networks. While centralisation may entail efficiency and convenience for information seeking, decentralisation may facilitate the distribution of critical information (Rulke and Galaskiewicz, 2000). However, it is important to note that decentralisation can occur in a variety of forms in information sharing networks. The following scenarios could all contribute to a centralised structure of information sharing in organisations: few members are sharing information with each other, a few are sharing information within cliques (i.e. small groups isolated from each other) (Bron and Kerbosch, 1973), and all members are uniformly sharing information with each other.[4] Organisations should circumvent the first two forms of decentralisation, in which information sharing is scarce and isolated. Instead, the management should cultivate the third form of decentralisation that is based on a broadly distributed structure of information sharing and knowledge transfer (DeSanctis and Monge, 1999).

Second, based on our finding of a centralised structure of information retrieval in participating teams, we recommend that organisations should provide and reinforce institutional assistance to alleviate the overload of information requests on knowledge providers, and to facilitate the knowledge transfer process. For example, organisations can hire secretarial staff who would serve as a liaison between information seekers and providers. These designated personnel can assist the gathering and organising of information requests, and help with the logistics of information provision. Moreover, organisations can implement a digital information infrastructure that provides an outlet for knowledge providers to publish their willing-to-share information (Hollingshead and Contractor, 2002). In this way, knowledge providers' burdens may potentially be reduced by directing information seekers to this digital form of information commons. More importantly, information seekers can access these knowledge sources even when they do not know who the experts are or when the experts are unavailable (Yuan et al., 2007).

However, organisational practitioners and scholars should pay attention to organisational members' motivation as well as hesitation in using digital information systems for information seeking and sharing. A case study found that a major reason for the lack of use and contribution to the digital knowledge management system at Ernst & Young was that many consultants were concerned about the privacy and safety in sharing confidential information through the digital information infrastructure (Sarvary and Chard, 1997). Research also suggests that organisational trust would exert a greater impact on information contribution than on information retrieval on digital knowledge repositories, because it is more difficult for information contributors to predict how their information would be used than for information seekers to evaluate the credibility of potential knowledge sources (Bock et al., 2008). In addition, it is found that individuals' technology-specific competency and the ease of using digital knowledge systems would motivate people to use and contribute to organisational intranets (Yuan et al., 2005).

Therefore, to fully leverage the power of digital knowledge infrastructures, we need to further understand how perceived benefits and costs associated with technology-mediated knowledge retrieval differ from those in interpersonal information transaction.

Finally, our study found that when employees perceived greater value in knowledge sharing, they were more likely to allocate information to other members and contribute to organisational information commons. In addition, previous research has found a positive direct impact of Organisational Learning Culture (OLC) on organisational performance (Škerlavaj et al., 2007). Thus organisations should nurture a culture that values knowledge sharing and transfer, such as providing financial and promotional incentives to employees who actively and effectively engage in information allocation and retrieval.

7.5 Limitations and future directions

One major limitation of our study is the lack of consideration for the effects of individual motivation on knowledge learning and sharing. While there exists a rich body of research on the relationship between motivation and knowledge sharing (Osterloh and Frey, 2000; Wittenbaum et al., 2004; Quigley et al., 2007), we did not include motivation as an antecedent variable in our conceptual and analytical model. The primary reason was that our current research did not have a valid instrument to measure individual motivation for information retrieval and allocation. Our future research will focus on developing reliable and valid measurement scales to properly test the effects of motivational factors on organisational learning and knowledge transfer networks, with particular attention to the differences between intrinsic and extrinsic motivation (Kaše et al., 2009), as well as cooperative (organisational) and competitive (individual) motivation (Wittenbaum et al., 2004).

Another limitation of our study is the exclusion of digital knowledge repositories in the knowledge and learning network. Scholars have advocated for more research on the effects of digital knowledge repositories on knowledge retrieval and transfer (Hollingshead et al., 2002; Monge and Contractor, 2003). In effect, researchers have conceptualised and distinguished *connective* and *communal* knowledge sharing in transactive memory systems (Fulk et al., 1996; Yuan et al., 2007). Connective knowledge sharing refers to direct person-to-person information exchange, whereas communal knowledge sharing refers to retrieving and publishing information through a collectively accessible knowledge repository, such as intranets and databases. Therefore, future research should further explore how humans interact with technologies for information retrieval and sharing. However, we should be cautious that technologies per se are at best necessary, but by no means sufficient, conditions for nurturing and sustaining organisational knowledge networks (Brown and Duguid, 2000; Cross and Baird, 2000; Contractor et al., 2004).

Like much other research on knowledge and learning networks, our study takes a cross-sectional approach. One disadvantage of analysing one-time network data is our reservation in determining the direction of causal relationships between the focal variables. For example, in testing the outcome model *H6a*, we are challenged by the possibility that it is members' enhanced satisfaction with their teamwork that affects their information retrieval, rather than in the opposite direction (*H6a*). Thus future research should employ a longitudinal approach to better capture the causal and evolutionary properties of knowledge and learning networks.

Although employees' job satisfaction is an important outcome variable in organisational research, we should further investigate other outcomes of knowledge and learning networks, such as work productivity and organisational performance. Miner and Mezias (1996) suggest that organisational learning may not always produce good outcomes. Scholars have encouraged further research on examining the potential benefits of a well-established transactive memory system, especially on enhanced organisational performance (Cross and Baird, 2000; Hollingshead and Brandon, 2003). After all, a key criterion to evaluate the effectiveness of organisational learning and knowledge transfer is how well the team performs its job tasks. Finally, although this study was carried out in nine organisational work teams, it was restricted to consulting professionals working in Western cultures. Therefore, to enhance the external generalisability of our study, future research should expand the scope and nature of participants to include members from a broader range of industries and cultures, such as a comparative analysis of organisational learning processes in different cultures (Dimovski et al., 2008). More importantly, it is essential to utilise multilevel and meta social network analysis to investigate the differences between multiple work teams and organisations, and how such variations would affect team members' information retrieval and allocation behaviours (Lubbers, 2003; Lubbers and Snijders, 2007).

8 Conclusion

Knowledge acquisition and information distribution are integrally linked to organisational learning (Huber, 1991). Our study demonstrates the theoretical and practical value of using a social network perspective to examine intra-organisational information retrieval and allocation. It is evident that the structures, antecedents and outcomes of team members' knowledge acquisition and distribution can be and should be explained by a multi-MTML framework. As social interaction becomes a critical vehicle for knowledge seeking and transfer (Cross et al., 2001; Casciaro and Lobo, 2005), a social network perspective has become a more appropriate and powerful tool for researchers to understand the underlying social processes that nurture and sustain organisational knowledge networks. For practitioners, we would like to encourage them to switch from a strategy of knowledge management to a strategy of managing knowledge networks (Contractor and Monge, 2002), which is based on an effective utilisation of distributed expertise within a network of individuals and knowledge repositories. After all, how to optimise the transfer and utilisation of individual knowledge (Brown and Duguid, 2000) to enhance individual performance and organisational effectiveness is our ultimate goal.

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Notes

1 The MTML framework is different from the traditional multilevel approach which focuses on explaining cross-level variations in hierarchically nested data (Kozlowski and Klein, 2000; Hox, 2002). The multilevel facet in the MTML framework examines various configurations of individuals as the unit of analysis, and how these configurations lead to diverse network structures.

2 The nature of our network data was multilevel. There were three levels associated with the information retrieval and allocation networks: knowledge domains nested within each team, and teams nested within each organisation. Since the goal of this paper was not focused on a cross-level analysis to examine the variations between knowledge domains and teams, we performed a meta-analysis at the team level only. We combined network data across all knowledge domains into a single network for each team, and used this single network as data input for ERGM analysis for each team. Specifically, we put knowledge-domain level networks on the diagonal of one large network, and filled the rest cells with structural zeros. We fixed the effects of these structural zeros in XPNet so that we only estimated the effects of the actual networks across multiple knowledge domains in each team. As an exploration, we did combine the network data across all knowledge domains of all teams into a single grand network (the highest level of our data). However, when we tried to perform ERGM analysis on the grand-level network, the XPNet program crashed due to the enormous size of the network (a 1207 by 1207 matrix), accompanied by a large number of parameters to be estimated (ten). In future research, one possible alternative is to use a multilevel analytic program MLwiN (Rasbash et al., 2005), which is designed specifically for meta-analysis of multilevel network data (cf. Lubbers, 2003; Lubbers and Snijders, 2007).

3 This hypothesis was strongly supported by the unanimously significant estimation of the in-k-star parameter, which tests the degree to which one member retrieves information from multiple others. In addition, our study reports (see Table 1) that the information retrieval network in our participating teams has a low mean density of 0.30 (compared to 0.52 of the information allocation network), which provides further support to *H3a*. Such results suggest that, although overall members did not actively retrieve information from others, those who did were most likely to retrieve information from the same member (the 'star'). This tendency has led to a highly centralised information retrieval structure in our participating teams.

4 We found the third form of decentralisation to be prevalent in our participating teams. The mean density (see Table 1) of the information allocation network across all knowledge domains and all teams is 0.52 (the maximum density of a network is 1). Network density is defined as the total number of ties divided by the total number of possible ties in a given network (Borgatti et al., 1999). It provides a descriptive measure of the frequency of the occurrence of network ties. A network density of 0.52 would reject the conjecture that the decentralised structure found in our study was simply the result of a sparse network of information allocation in our participating teams.

Appendix: Measurement items

1 *Frequency of information retrieval from team members*
How frequent have you retrieved information from other members in each of the following knowledge domains?

2 *Frequency of information allocation to team members*
How frequent have you allocated unsolicited information to other members in each of the following knowledge domains?

3 *Perception of the value of knowledge sharing (Cronbach's alpha = 0.73)*
To what extent do you agree or disagree with the following statement?

   1 I believe knowledge sharing is important.

   2 It is more important to work hard as an individual than to share knowledge. (*reversely coded*)

   3 Employees with knowledge sharing skills are strategically important to the company's ability to compete in the marketplace.

   4 In this firm, people that share their knowledge have greater opportunities to receive promotions.

4 *Satisfaction with teamwork (Cronbach's alpha = 0.81)*

   1 How satisfied are you with how well your group coordinates who will do what?

   2 How satisfied are you with how well your group works together as a group?

   3 How satisfied are you with the efficiency of your group in completing projects?

5 *Job position*
Which category best describes your job type?

   1 Managing consultant

   2 Analyst consultant

   3 Consultant

   4 Senior consultant

   5 Manager

   6 Senior manager.