

Intra-organizational learning networks within knowledge-intensive learning environments

M. Škerlavaj^{a*}, V. Dimovski^a, A. Mrvar^b and M. Pahor^a

^a*Faculty of Economics, University of Ljubljana, Slovenia;* ^b*Faculty of Social Sciences, University of Ljubljana, Slovenia*

(Received 23 January 2008; final version received 5 May 2008)

Organizational learning contributes to organizational performance. One research question that remains inadequately explained is how learning occurs. Can it be explained by using the acquisition or participation perspectives? Or is there a need for some other view? This paper suggests that learning networks form an important learning environment for knowledge transfer. A case study of a software development and business consulting company is used to test the network perspective on intra-organizational learning. Both exploratory and confirmatory social network analysis of a learning network within the IT company are used to establish learning patterns within organizations. Learning needs to be seen as both participation in communities of practice and a flow of previously acquired knowledge.

Keywords: organizational learning; network perspective; social network analysis; exponential random graph modeling; knowledge-intensive learning environment

Introduction

The pioneers in the field (Argyris & Schön, 1996; March & Simon, 1958) defined organizational learning as individuals' acquisition of information, knowledge, and analytical and communicative skills. Seeing organizational learning as a scalable process, the learning organization (Senge, 1990) is a structure and an ideal form of organization which can be achieved when the process of organizational learning is fully optimized and when the organization is viewed as a system. This focus on the individual acquisition of skills and knowledge as a point of departure for organizational learning and the learning organization has been criticized for focusing upon individual mental processes and a concept of knowledge that stresses the importance of abstract thinking (Cook & Brown, 1999; Nicolini, Gherardi, & Yanow, 2003). As an alternative, it has been proposed that learning takes place through participation in communities of practice and with a point of departure in concrete organizational practices. Apparently, these two divergent perspectives for organizational learning collide. In the acquisition perspective the mind is viewed as being a container, knowledge as a substance, and learning as the transfer and addition of substance to the mind, while the participation perspective derives from studies of learning in which no teaching was observed and which understand learning as participation in communities of practice (Lave & Wenger, 1991).

*Corresponding author. Email: miha.skerlavaj@ef.uni-lj.si

A leading researcher in the field of organizational learning stated that the ability to learn faster than one’s competitors may be the only sustainable competitive advantage (De Geus, 1988). Easterby-Smith, Crossan, and Nicolini (2000) even compared the organizational learning realm to “volcanic activity” in which multiple foci of interest coexist all the time, some of which are active, while others are passive but may resurface at any time. Bapuji and Crossan (2004) made great progress in empirical research into organizational learning phenomena. Škerlavaj, Indihar Štemberger, Škrinjar, and Dimovski (2007) provided empirical support for the notion that higher level organizational learning contributes to increased value added per employee, the return on assets, employee and customer satisfaction, and the quality of relationships with main suppliers. Knowing that higher level organizational learning contributes to organizational success, one research question that remains inadequately explained is how learning occurs. Can it be explained using the acquisition, participation, or some third perspective as, for instance, Elkjaer (2004) suggested?

This paper has four main parts. First, it contrasts the acquisition and participation perspective with organizational learning and upgrades them with the learning network perspective. Second, it classifies various types of learning networks according to learning network theory. Third, it tests the learning network perspective using social network analysis of a software development and business consulting company. Finally, it discusses the results and concludes by exposing some limitations and by providing directions for future research in the field.

Acquisition and participation perspectives on organizational learning

Elkjaer (2004) suggested that two perspectives on organizational learning collide. Table 1 contrasts the acquisition and participation perspectives on organizational learning.

Table 1. Three views of organizational learning.

	Acquisition perspective	Participation perspective	Network perspective
Learning content	To be skilled and knowledgeable about organizations	To become a skillful practitioner in organizations	To be skilled and knowledgeable about organizations and to become a skillful practitioner in organizations
Learning method	Acquisition of skills and knowledge	Participation in communities of practice	Acquisition of skills and knowledge and participation in communities of practice. The learning process needs to be contextualized within the framework of other social processes
Organization	System	Communities of practice	Social worlds

Source: Adapted from Elkjaer (2004) and Lazega (2001).

The acquisition perspective underlies much of the early literature on organizational learning (Cyert & March, 1963; Huber, 1991; March and Simon, 1958), and especially literature on the learning organization (Pedler & Aspinwall, 1998; Senge, 1990). This view on organizational learning comprises an understanding of learning as the individual acquisition of knowledge and skills. The mind is viewed as a storage place, knowledge as an essence, and learning as the transfer and accumulation of that essence to the mind. This understanding of learning is predominant because it reflects an understanding of learning known from formal education. As such, this understanding has become the “folk theory” or “common sense” understanding of learning (Hager, 2004).

On the other hand, the participation perspective derives from practice-based studies (e.g. apprenticeship learning) in which no teaching was observed (Lave & Wenger, 1991). Within this perspective, learning is understood as participation in communities of practice – as a movement from an old-timer to a newcomer. The participation perspective takes learning out of the individual mind and formal education settings and places it in everyday organizational life and work.

Still, there are some indications that these two perspectives are too incomplete to allow a full understanding of organizational learning. Elkjaer (2004) departed from pragmatic theory and suggested the so-called “third way,” which is an attempt to make a synthesis of the “second way” as seen in the participation perspective and communities of practice by including elements of the “first way” of organizational learning, learning as the acquisition of knowledge as well as analytical and communicative skills. The authors agree that the content and the process of learning are not “visible” as in a chemical experiment and that learning takes place as a social process, rather than as a system or just in communities of practice.

Nevertheless, the “third way” seems to put too much emphasis on the participation perspective and neglects some vital aspects of the acquisition perspective. In the learning network perspective, as proposed in our contribution, a synthesis needs to be performed in such a way that the individual is recognized as the primary source and destination for learning (the “first way”), while acknowledging that learning takes place primarily in social interaction (the “second way”). Hence, the authors argue that the learning network perspective seems to best describe organizational learning. Furthermore, a broader structural theory of collective action (Lazega, 2001) needs to be considered in the context of organizational learning, while managing to connect the individual perspective with the organizational one. According to this theoretical framework the learning process needs to be contextualized as one of the processes that unfolds along with others and has to be related to those processes.

Learning networks

Cross, Parker, Prusak, and Borgatti (2001) argued that a significant component of a person’s information environment consists of the relationships they can tap for various informational needs. The paper expands this informational view to the learning perspective and introduces the concept of the learning network. Learning networks can be classified as internal and external (Birkinshaw & Hagström, 2002). The former are seen as an extended enterprise model and comprise relationships that a firm has with its customers, suppliers, and other stakeholders. This paper focuses on the latter form of internal organizational learning networks, which in our case form a set of internal relationships among individual members of the firm and other constituencies, such as product/service divisions and geographical units.

Learning network theory (Poell, Chivers, Van der Krogt, & Wildermeersch, 2000; Van der Krogt, 1998) describes the way learning is organized within the context of work organizations. According to this theory a learning network operates in every organization. Learning networks are not limited to network-type organizations, matrix organizations, or team-based organizations. People learn in every organization, even in a hierarchical or chaotic one, and the learning network merely represents how learning is organized. A learning network consists of the various learning activities organized by the members of the organization. The three main components are: (1) learning processes – the development of learning policies, the development of learning programs, and the execution of learning programs; (2) learning structures – content structure, organizational structure, and learning climate; (3) actors – employees, managers, etc. Learning networks can take various shapes depending on both actor dynamics and work characteristics. The four various theoretical types of learning networks and their characteristics are presented in Table 2.

The liberal learning network is very likely to emerge within organizations that take the notion of individual employee empowerment seriously (Andrews & Herschel, 1996). The notion of employability can be equally regarded as a tendency leading towards liberalization (Bloch & Bates, 1995; Filipczak, 1995). The vertical learning network is common in many large organizations and, despite the growing unpopularity associated with Taylorism, it still plays a dominant role in organizational reality (Wilson & Cervero, 1997). The horizontal learning network has gained popularity through extensive literature on learning organizations, up to the point where the total integration of learning and work

Table 2. Four theoretical types of learning networks.

	Learning networks			
	Liberal	Vertical	Horizontal	External
Learning processes	Single activities	Linearly planned	Organically oriented	Externally coordinated
Development of learning policies	Implicit	Planning	Learning	Inspiring
Development of learning programs	Collecting	Designing	Developing	Innovative
Execution of learning programs	Self-directing	Guiding	Counseling	Advisory
Learning structures				
Content structure (profile)	Unstructured (individually oriented)	Structured (task or function oriented)	Open or thematic (organization or problem oriented)	Methodical (profession oriented)
Organizational structure (relations)	Loosely coupled (contractual)	Centralized (formalized)	Horizontal (egalitarian)	Externally directed (professional)
Learning climate	Liberal	Regulative	Integrative	Inspiring

Source: Adapted from Van der Krogt (1995, 1998) and Poell et al. (2000).

in teams seems to be advocated (Senge, 1990). The external learning network is common in environments where employees have a strong orientation to their professional field. Managers find it hard to control and deem it inflexible, while it seems to be popular among employees since the professions usually offer their members greater status and job security (Poell et al., 2000).

Social network analysis of a learning network within an IT company

Company and sample profile

In order to understand the learning network perspective the authors conducted a social network analysis (SNA) within a software company that had 93 employees in three geographical units (Slovenia, Croatia, and Serbia and Montenegro). The company was founded in 1989, a subsidiary was introduced in Croatia in 2000, and a joint venture in Serbia and Montenegro in 2003. It had €4.2 million in turnover in 2004, and average annual growth of 28% in the period 1995–2003. Their core business comprised software development, IT and business consulting, and maintenance and support. The three main business units (BU) were Enterprise Resource Planning Solutions, Industry Solutions, and Banking.

Fifty-nine respondents worked in Ljubljana (Slovenia), 11 in Zagreb (Croatia), and another 11 in Belgrade (Serbia and Montenegro). For a knowledge-based organization it is important to have an adequate educational structure. In our case 56.7% of the respondents have a university degree or higher (even one Ph.D.), while a significant proportion of the employees are high school graduates still in the process of formal education. Seventy-four percent of the respondents were male, the average tenure in the company was 38.9 months (varying from 1 month to 15 years). The company had a relatively flat organizational structure, with just a few hierarchical levels and wide control spans. Of the respondents, 60.5% declared themselves to be non-management, 8.6% to be line management, 6.2% to be middle management, 17.3% to be project management, and 7.4% to be top management. The most common function was that of programmer (software developer, tester, software architect), involving 34.6% of the respondents, followed by consultant, representing 24.7% of the respondents, and project manager, at 9.9%.

Methodological framework – social network analysis

Data for measurement of the learning network was generated by asking respondents who the people are in their organization from whom they learnt the most. They were given a coding scheme with the names and identities of all employees and co-workers within the company. The level of learning was represented on a 1 to 5 scale, where a value of 1 meant “I do not learn from this person” and 5 signified “I learn a lot from this person.” Ninety-three units in the network received the questionnaire via e-mail in December 2004. After one month and a second call 81 fully completed questionnaires were obtained. The 12 members of the organization who failed to participate were either on parental leave or recent newcomers and were estimated not to have had a significant impact on the current state of the learning network within the company. Recoding was undertaken so that those responses with a value on the scale of less than 3 (meaning they learnt little or very little from that person) were given a value of 0 and others a value of 1. Hence, the response rate was 87.1%. Data validity and reliability were assured using an in-depth interview with a member of middle management who confirmed the fit between his subjective view of the matter and the results of the SNA.

Social networks are seen as a specific set of linkages among a defined set of people, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behavior of the people involved (Mitchell, 1969). The social network approach views organizations in society as systems of objects (e.g. people, groups, and organizations) joined by a variety of relationships. Not all pairs of objects are directly joined, and some are joined by multiple relationships. Network analysis is concerned with the structure and patterning of these relationships and seeks to identify both their causes and consequences (Tichy, Tushman, & Fombrun, 1979). Network analysis examines the system-wide effects, instead of the characteristics of actors. As an alternative to viewing a relationship in isolation, it treats a relationship as a gateway to other relationships through which knowledge or resources may be reached (Easton, 1992). SNA provides a visualized graphic and mathematical analysis of a complex human interaction and entails the mapping and measuring of relationships and flows between people, groups, organizations, computers, or other information/knowledge processing entities. The nodes in the network are people and groups, while the links represent relationships or flows between the nodes. Rather than focusing on the permanent attributes of people, objects or events, the social network perspective views the characteristics of these people as arising out of a relational process (Wasserman & Faust, 1994).

SNA is a multilevel analysis and uses such various concepts at the actor, dyadic, triadic, subgroup, and global network levels of analysis to explain network-related relationships (such as intra-organizational learning). At the individual level of analysis in-degree centrality represents the number of directed ties (arrows) that terminate at a certain node (Monge & Contractor, 2003). Related to learning networks, the higher the in-degree centrality of a person A the higher the number of people that claim to be learning from person A. Betweenness centrality measures the extent to which a node (person) is directly connected to those other nodes that are not directly connected to each other. Hence, organizational members with high betweenness centrality act as bridges or liaisons between different parts of the company and are important to obtain cross-functional, heterogeneous types of knowledge. At the dyadic level of analysis, reciprocity (symmetry) is the extent to which a relationship is bi-directional (Brass, 1995). For instance, if A is a friend of B, B is also a friend of A. At the triadic level of research, transitivity is related to three actors who are transitive whenever A is linked to B, B to C, and C to A. At the subgroup level of analysis, cliques are network sub-patterns where all the nodes are fully connected to each other. For instance, within a three clique learning network there are three people A, B, and C who all learn from each other. At the global network level of analysis, network centralization is defined as the difference between the centrality scores of the most central actor and those of all other actors in the networks, and is used to form a ratio of the actual sum of the differences to the maximum sum of differences (Brass, 1995). Network centralization ranges from 0 to 1 and shows the level to which a certain network is centralized or not. Network density is the ratio of the number of actual links to the number of possible links in the networks (Brass, 1995). Both network centralization and density are used to compare different (sub)networks and are influenced by the network size (the number of nodes within the networks).

Exploratory network analysis

An inter-personal network with a three business and three geographical unit organization and which measured the “learning from” relationship is presented in Figure 1. The software used for the descriptive network analysis was Pajek 1.18 (Batagelj & Mrvar, 1996,

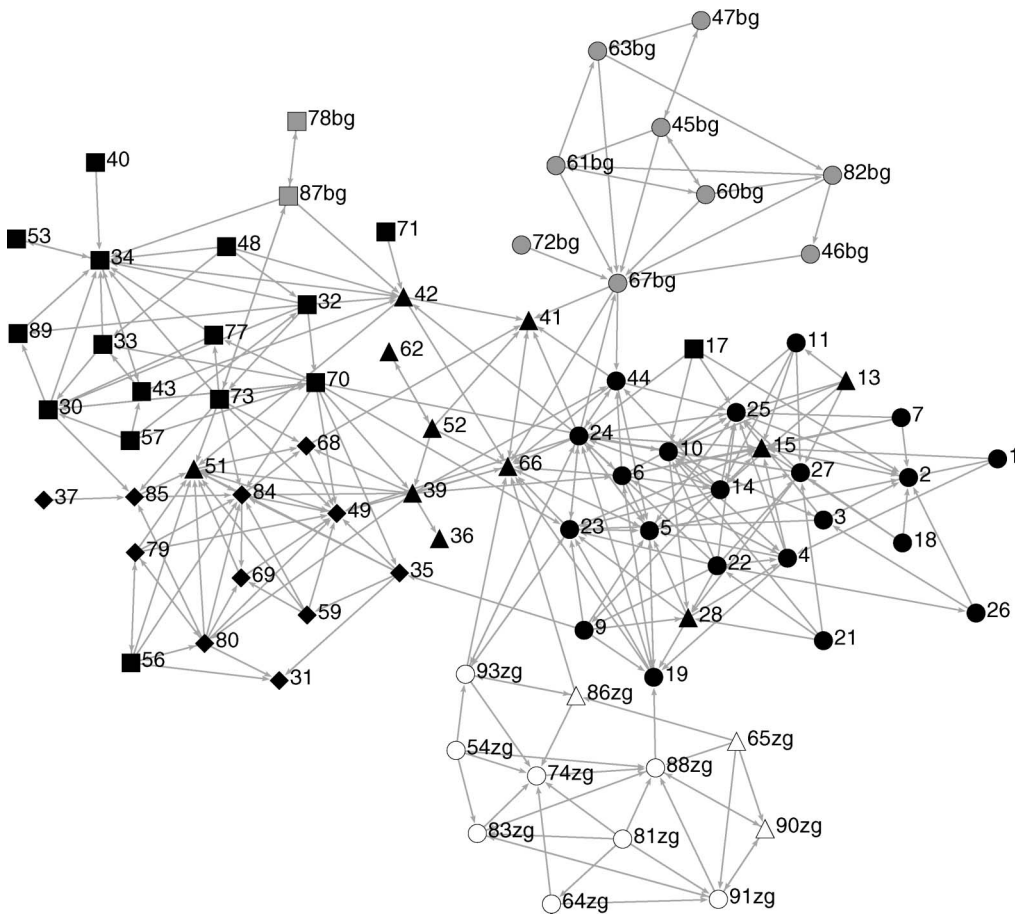


Figure 1. Visual representation of the learning network in the company analysed.

1998; de Nooy, Mrvar, & Batagelj, 2005). An arrow leading, for instance, from person 52 to person 66 means that person 52 learns from person 66. The shapes of the units represent the department they belong to, whereby a circle is Navision, a square is Banking Solutions, a diamond Industry Solutions, and a triangle denotes Other departments. In addition, the colors of each unit stand for the location they work at (white means Zagreb, black Ljubljana, and gray Belgrade).

Figure 1 indicates that there might be a relatively strong inter-connectedness within the three various locations, while the connections among them are quite rare. For instance, within the Croatian subsidiary only three people learn from their co-workers in Ljubljana, while in Belgrade just two such people existed. Learning in the other direction was even scarcer. It is interesting that there were no learning relationships between Belgrade and the Zagreb subsidiary. In part, this can be explained by the fact that the Belgrade unit was established later. Explicit knowledge was transferred to Belgrade above all from Ljubljana personnel, who still controlled the majority of their operations. At the same time, most “international” projects went to Belgrade from Ljubljana. Such projects are known to have the strongest impact on learning and knowledge transfer.

The company invested heavily in the development of informal relationships among employees, including the subsidiaries. Despite this, the transfer of tacit knowledge was mainly restricted to the exchange of ideas about certain expert problems, while the transfer of explicit knowledge was confined to start-up support with projects. The probable reason for this situation was that the employees in Ljubljana were under great pressure and the budget for cooperation was not defined. It was all built on a voluntary basis. Hence, the company might have reconsidered its reward system in order to provide incentives for cooperation and learning, given the proven fact that organizations with a higher level of organizational learning gain in terms of an increased level of return on investments, value added per employee, and improved quality of relationships with employees, customers, and main partners (Škerlavaj et al., 2007).

It is also quite obvious from Figure 1 that learning among the various business units occurred much more than among the various geographical units. The problem of insufficient horizontal communication, significant for traditional, functional, or divisional organizational structures, was in this case well resolved. This could be attributed to the intensive informal contacts among the leaders and the age similarity of the employees.

The analysis of the degrees of input and output of members of the learning network revealed several issues. Regarding the degree of input, the members (units) with the largest degree of input were people who had the most experience in the field. Other members of the Ljubljana sub-network learnt most from the most experienced and competent co-workers, who were at the same time also directors of business units or project managers, and in one case even a member of the top management team. The same went for Zagreb and Belgrade – experience was the strongest criterion for being a source of learning for other people. A common characteristic of those people with the highest degree of input in Ljubljana was their, on average, 66 months of tenure within the company, which was twice the average of all employees. It also needs to be emphasized that the majority of people in the company with a high degree of input belonged to middle management and had up to 10 years of tenure within the company, while others (with 2–3 years of tenure) were the top human resources of competing companies. They were head-hunted by this particular company and after a few months of adaptation took over leading positions. Employees with the lowest number of input degrees were beginners, still university students, or administrative personnel. According to the interview in only a few cases could a low input degree be attributed to the employee's high specialization or introverted character. High output degrees pointed to members of the network who learned from the largest number of employees.

The analysis of the strong components within the network shows that learning occurred mainly among business units – on the one hand, ERP Solutions and, on the other, Industry and Banking Solutions. SNA also revealed four cliques on three vertices (these are units that learnt from one another). Interestingly, in one case these were people who worked in the same room, while in the three other cases these were people with a similar level of expertise who complemented each other regarding their personal characteristics and the knowledge they possessed. There were only two larger strong components that could be partially explained by belonging to a geographical location, one with 50 vertices and the other with vertices from the Belgrade group (45bg, 47bg, 60bg, 61bg, 63bg, and 82bg). All other components were composed of two or fewer vertices.

Table 3 shows the network and sub-network densities as well as average input degrees. Density takes a numerical value between 0 and 1. A network would have a value of 1 when all the vertices are connected to all the other vertices. Not surprisingly, smaller networks are denser than larger sub-networks. Perhaps it is notable that the Zagreb unit was denser

Table 3. Network and sub-network densities and average input degrees.

Network	Density	
Whole learning network	0.046	
Sub-networks: partition criteria	Sub-network density (sub-network size)	
Geographical location	Ljubljana: 0.068 (59)	Zagreb: 0.25 (11)
Gender (60)	Male: 0.0541(21)	Female: 0.0544
Department (38)	ERP Solutions: 0.088 (18)	Industry Solutions: 0.117 (14)
Hierarchical position	Top management: 0.25 (6)	Middle management: 0.28 (5)
	Average input degrees	
Geographical location	Ljubljana: 4	Zagreb: 2.73
Department	ERP Solutions: 3.34	Industry Solutions: 2.11
Hierarchical position	Top management: 1.50	Middle management: 1.40
	Project management: 1.00	Belgrade: 2.09
	Line management: 0.29	Banking: 2.09
	Personnel: 1.86	Other: 1.14
	Line management: 0.041 (7)	Project management: 0.07 (14)
	Personnel: 0.038 (49)	Other: 0.082

than the Belgrade one (being of equal size). This can be attributed to the fact that relationships need time to be established and that the Belgrade unit was relatively new. According to gender criteria, no significant differences in sub-network density existed, while differences among departmental sub-network density could be attributed to differences in their size. The same could be said for hierarchical position.

Average input degrees might add some information to the sub-network densities. While every member of the Ljubljana sub-network had on average 4 people who learnt from him, this figure was lower for the Zagreb (2.09) and Belgrade (2.73) sub-networks. Not surprisingly, members of the Ljubljana sub-network were more often a source of learning than the Zagreb and Belgrade sub-networks, due to differences in size. Similar conclusions were reached by analyzing the average input degrees of sub-networks by department partition. Members involved in older, core businesses (ERP Solutions) were on average more often sources of learning than was the case for other departments. The fact that input degree increased as one climbed up the corporate ladder was also encouraging. When analyzing average input degrees one has to be aware of the limitation that only relationships among members of certain groups (business, geographical, or hierarchical) are accounted for. Nevertheless, the same computation principle allows a comparison between various criteria. Knowing that all average in-degrees according to hierarchical position are lower than the department average in-degrees leads us to think that there are more connections among various hierarchical positions than among departments. In Appendix 1 matrices showing the number of connections within and between various groups according to the criteria of geographical location, department, and hierarchical position are provided.

When observing brokerage roles researchers scrutinize triads of vertices and the relationships among them according to the group they belong to. We analyzed brokerage roles according to the criteria of geographical location, which proved to have the strongest impact on learning in an earlier examination of the gathered data. The coordinator is the person who connects two members of the same group who do not learn directly from each other. The learning flow goes indirectly through the coordinator. This role is seen most often (71 times) regarding unit 24 (director of ERP Solutions development). This is no surprise given that this is one of his duties and that coordination is one of his explicit responsibilities. Another six people played this role more than 20 times, while 27 people never played the role of coordinator.

An itinerant broker has a similar role to a coordinator, with the distinction that this person does not belong to the same group as the other two. In simple terms, an itinerant broker returns knowledge to the group from which he got it in the first place. All four itinerant brokers were members of the subsidiaries and were co-workers who participated in common projects with members from the central office in Ljubljana. Ten members of the organization played the role of a gatekeeper. They learned something from a member of their sub-network and then passed it on to a member of another subgroup. Only one person was a liaison, someone who connected members of various subgroups, while he did not belong to any one of them. In our case unit 24 (director of ERP development) learnt from person 67bg (Belgrade unit) and then passed this knowledge on to person 93zg (from Zagreb).

The betweenness centrality of a vertex is the proportion of all geodesics between pairs of other vertices which include this vertex (de Nooy et al., 2005). This measure is important for communication networks, within which learning networks can also be included. It points to those members of networks who lie on the shortest routes among pairs of units within the networks and, as such, have control over information flows.

Table 4 shows the 15 most important vertices according to the betweenness centrality criteria. As expected from the brokerage roles analysis, the most important vertex is unit 24 (director of ERP Solutions development), followed by unit 42 (director of the department). Both of them were members of top and middle management. This confirms the fit between formal and informal organizational structures from the learning perspective. The first member of personnel, a programmer (vertex 34), was in third place. The most central units from Belgrade and Zagreb were in the eleventh and fifteenth places. 88zg was a consultant, while 67bg was a member of a top management team. The betweenness centralization of the whole network equaled 0.30.

Blockmodeling is concerned with the search for groups within the network that have a similar structure of relationships among vertices. Wasserman and Faust (1994) defined various theoretically relevant block models. Among others, these include cohesive groups, the center–periphery model, the central model, and the hierarchical model. According to previous studies (Lazega, 1992), knowledge-based organizations should have a structure of relationships closer to cohesive groups, while large (mainly manufacturing) systems are supposed to look similar to hierarchical models. Cohesive groups have strong connections within each group and are virtually without connections between different groups. The center–periphery model has one central group within which units are strongly connected and they are also connected to members of other groups. Other peripheral groups are connected to this central group and not within their groups. A central model is a special case of the center–periphery model whereby connections among peripheral groups are not allowed (Doreian, Batagelj, & Ferligoj, 2005).

The analysis of block models according to geographical location partition (three subgroups) and departmental partition (four groups) revealed that the theoretical model which fitted the data best was the model of cohesive groups. This statement can be supported from both the analytical and substantive perspectives, given that it is a knowledge-based organization. One cannot claim there is a hierarchy in the learning network in the case of the company investigated. Another argument in support of the network's cohesiveness is the fact that vertex 67bg is the only true articulation point – removing this vertex from the network causes the main part of the Belgrade group (except for 78bg and 87bg) to be disconnected from the rest of the network. On the other

Table 4. The 15 most important vertices according to betweenness centrality (C_B) criteria.

Rank	C_B	Vertex name
1	0.34	24
2	0.21	42
3	0.19	34
4	0.16	30
5	0.15	43
6	0.14	66
6	0.14	5
6	0.14	33
6	0.14	70
10	0.08	41
10	0.08	88zg
10	0.08	93zg
13	0.07	68
13	0.07	19
15	0.06	67bg

hand, most of the vertices in the Ljubljana and Zagreb groups belong to the same bi-connected component.

Regarding the center–periphery, blockmodeling revealed an almost six clique center composed of units 5, 6, 14, 24, 25, and 44. Their common characteristics were that they belonged to the ERP Solutions department (core business), almost all of them were middle or project managers, had an above average tenure in the company or industry, and were well educated (ranging from B.Sc. to M.Sc.). Despite the existence of a center within the network, the model of cohesive groups still fitted the data best. The formation of cohesive groups within the company was much more a result of geographical location than departmentalization. At the same time, hierarchical clustering (Ward’s method on corrected Euclidian distance) produced a dendrogram (Appendix 2) from which it is quite obvious that the units are formed according to geographical criteria. While they succeed in overcoming interdepartmental barriers, they need to address the issue of mechanisms for learning among the various geographical locations.

Effects governing the learning network’s structure

Based on the existing theoretical background described in the initial chapters of this paper, five hypotheses for testing were formulated.

Learning as participation occurs by participating in communities of practice (Lave & Wenger, 1991), which in networks can be found as dense sub-networks (e.g. cliques).

H1. Learning in the network will mostly occur in cliques

In order for learning to occur (and this applies especially to learning as participation) the participants must have the opportunity to learn. An opportunity to learn from someone always happens when two people meet or work on the same or similar problems. Thus, working in the same location or in the same department should create opportunities to learn and thereby foster learning.

H2. An opportunity (i.e. working in the same location or in the same department) will increase the probability of learning

As more experienced workers have more to teach to the less experienced ones and need to be taught less, it is to be expected that more experienced workers will have higher in-degrees (meaning that they have more arrows pointing to them) and lower out-degrees (having more arrows pointing out from them) in the network. In view of Lave and Wenger’s (1991) movement from old-timer to newcomer in communities of practice (CoP), workers with a longer tenure are already old-timers and newcomers learn from them, even if no teaching is observed.

H3. More experienced employees will be more sought after to learn from and have less of a need to learn from others

One would expect that in order to please a superior one would learn from the superior and then perform accordingly. Thus, one can expect that people higher up the hierarchical ladder will have higher in-degrees, as their subordinates will tend to learn from them. However, climbing up the hierarchical ladder should not diminish one’s ability or desire to learn from others.

H4. People higher up the hierarchical ladder will be more sought after to learn from. However, they should learn as much or even more than those on lower levels

Scientists involved in social network analysis often describe homophily as one of the leading factors in the establishment of social networks (see, for example, McPherson, Smith-Lovin, & Cook, 2001). Homophily can be explained with the adage that “birds of a feather flock together.” Research in communications networks (including learning and knowledge networks) almost uniformly refers to idea of homophily, i.e. the selection of others who are similar when forming relationships. Homophily has been studied in terms of similarity in gender, education, tenure, occupation, etc. (Brass, 1985; Ibarra, 1992, 1993; McPherson and Smith-Lovin, 1987; McPherson et al., 2001). People normally tend to form ties with those who are similar to them. We will examine homophily in terms of same gender, similarity in experience (tenure), and belonging to the same hierarchical level in the formal hierarchy.

H5. Homophily has an effect; it is more probable you will learn from those who are similar to you in terms of gender, tenure, and/or hierarchical position

The learning relationship described above can be represented by a dichotomous digraph (directed graph). We attempted to model the rules that govern the existence of specific learning ties between the actors in our network. This was done by using the logistic model for social networks known as the exponential random graph model (Snijders, 2002; Snijders et al., 2006) or the p^* model (Wasserman & Pattison, 1996). The model basically assesses the probability of the existence of a tie between two actors given the structural properties, the properties of each actor, and the properties of dyads.¹ The mathematical form of the model and the statistics tested are given in Appendix 3. In order to test the proposed hypotheses we used seven different models in which we added the effects stepwise (see Table 5). When selecting the effects included we largely relied on the estimations found in Snijders et al. (2006) for the friendship relation between lawyers taken from the study by Lazega (2001).

In the initial model we included the basic structural effects, reciprocity,² and in- and out-stars effects. In the initial runs of the model we had problems achieving model convergence. After consulting the literature (Snijders et al., 2006) we decided to include some new specifications of the parameters for the exponential random graph model, namely alternating k-stars. The in- and out-2-stars model the actors' propensity to have more relations, while the alternating equivalents check for variations in in- or out-degrees. The second model introduces more structural effects, namely two-paths, alternating k-paths, and alternating triangles in order to see if clustering is present in the learning network. Besides the structural effects, models 3 and 4 introduce the opportunity effects of being in the same location or in the same department. Both are modeled as dyadic covariates – in the covariate a tie exists if two actors are in the same location (in the same department). Model 5 introduces the effect of experience, which is included as years of tenure within the company. Both experience-related activity and popularity are investigated. Similarly, in Model 6 seniority-related activity and popularity are investigated. Seniority is included as a hierarchical position that has five stages, with low numbers indicating higher positions. The final model brings in the effects of similarity. Three similarity measures are included: gender, tenure, and seniority similarity. Although the current implementation of the methodology lacks proper goodness of fit measures, the addition of similarity effects does seem to significantly improve the model, judging by the

Table 5. Results of estimations.

Effect	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Structural	Reciprocity	2.26 (0.19)	0.96 (0.31)	0.83 (0.32)	0.74 (0.29)	0.69 (0.28)	0.66 (0.30)
	Out-2-stars	0.06 (0.05)	0.05 (0.03)	0.04 (0.03)	0.05 (0.04)	0.05 (0.04)	0.05 (0.03)
	In-2-stars	0.07 (0.02)	0.01 (0.02)	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)	0.01 (0.02)
	Alternating out-k-stars, $\lambda = 2$	-0.04 (0.32)	-0.95 (0.30)	-1.15 (0.31)	-1.07 (0.32)	-1.22 (0.32)	-1.11 (0.34)
Clustering	Alternating in-k-stars, $\lambda = 2$	0.96 (0.18)	0.23 (0.18)	0.27 (0.18)	0.26 (0.18)	0.21 (0.17)	0.21 (0.19)
	2-paths Alternating k-triangles, $\lambda = 2$		-0.03 (0.03)	-0.01 (0.03)	-0.06 (0.03)	-0.04 (0.03)	-0.07 (0.04)
Opportunity	Alternating independent 2-paths, $\lambda = 2$		1.37(0.10)	1.18 (0.10)	1.07 (0.12)	1.06 (0.11)	1.04 (0.11)
	Same location Same department		-0.20 (0.04)	-0.22 (0.04)	-0.15 (0.05)	-0.16 (0.05)	-0.14 (0.05)
Experience	Tenure popularity			1.81 (0.25)	1.81 (0.25)	1.89 (0.27)	1.90 (0.26)
	Tenure activity			0.75 (0.10)	0.83 (0.10)	0.83 (0.10)	0.82 (0.12)
Seniority	Hierarchical position popularity					0.05 (0.01)	0.05 (0.02)
	Hierarchical position activity					-0.01 (0.02)	-0.02 (0.02)
Homophily	Same gender					-0.13 (0.04)	-0.20 (0.05)
	Close in tenure Close in hierarchical position					-0.05 (0.06)	-0.06 (0.06)

general increase in the parameter to standard error (*t*-statistic) ratios. Hence, using the nested model approach we tested and confirmed the reliability of the findings.

Confirmatory network analysis

The models were estimated using the Markov chain Monte Carlo procedure for estimating the exponential random graph model (Snijders, 2002). This algorithm allows the estimation of standard errors for parameters, besides the parameters themselves. This allows us to test the significance of the estimated parameters. The Metropolis–Hastings sampling procedure was used. Estimations are based on the Robbins–Monro algorithm for approximating a solution to the likelihood equation incorporated in the SIENA program (Snijders & Huisman, 2002), which is part of the STOCNET package (Boer, Huisman, Snijders, & Zeggelink, 2001), were applied.

The downside of the procedure is that, so far, no overall measure of the goodness of fit exists for the model. A possible indicator of the model's appropriateness is its convergence. If the algorithm works properly, the computed estimate is an approximation of the maximum likelihood estimate. However, Snijders (2002) discussed a number of problems in estimating the parameters of this distribution and for many data sets it is impossible to achieve satisfactory estimates (i.e. good convergence) with this method – perhaps it is next to impossible with any method. Also, the exact distribution for parameters is unknown. They are, however, believed to be distributed in an approximate *t*-distribution. Ratios between the parameter and the corresponding standard error (*t*-statistic) of two or more therefore indicate the statistical significance of the effects (Snijders, 2001).

All of the models were tested with at least two independent runs. On average the model estimations took close to 2000 iterations in phase two and 500 iterations in phase three (see Snijders & Huisman, 2002). The first model checked for the structural effects and the formation of cluster-like groups within the network. Reciprocity has an effect, indicating that a large share of learning is symmetrical, namely that actors learn from each other. However, this finding cannot be treated as conclusive, as similar analyses in other companies show different results when testing reciprocity in learning networks (Pahor, Škerlavaj, & Dimovski, 2008). Nevertheless, some kind of reciprocity is needed to form a social relationship (in this case, learning). It is human nature to expect something in return when offering knowledge to others. In this case, organizational members got some other kind of knowledge in exchange, while it is also not rare to gain status and respect in return for being a source of valuable knowledge.

There is a significant and positive effect of in-2-star effect, meaning that it is likely for actors to have several incoming ties, while the positive alternating in-*k*-stars effect indicates high variations in in-degrees. Apparently there were few very central organizational members from whom a majority of the people learnt, and there were also many others that were much less sought after for learning. The joint presence of in-2-star and alternating in-*k*-star effects confirms the presence of brokers, as evident in the descriptive analysis of the network. Brokers were the people who formed a bridge between different parts of the firm and were very important for connecting and conveying knowledge from one department, location, team, etc., to another. They were important for both creativity and cohesiveness within the organization as they acted as bridges between disconnected members of the organization.

The negative alternating independent *k*-paths and positive alternating *k*-triangles that were added in the second model show that the actors in the learning network formed clusters in which learning was much more intense. After adding these effects the in-stars

become non-significant. This indicates that the high in-degrees are caused by this clustering, so the brokers were important for the local cluster, but in general their importance was not so prominent. After accounting for the clustering effects, the relatively large effect of reciprocity from the previous model dropped significantly, since reciprocated ties in clusters are not so surprising. We expect that clusters within the learning network observed formed according to the geographical location and functional department, as well as the project teams the organizational members belonged to. This finding is confirmed by Models 3 and 4.

Model 3 adds the location covariate, which is significant and positive, indicating that most of the learning occurred at the same location. The same holds for the department covariate, which is added in Model 4. With the addition of these two variables the clustering indicators, as well as reciprocity, lose their strength somewhat, but remain significant. This means that some of the observed clustering can be explained by location and department, but most of it goes beyond that. For IT companies an important determinant of clustering could be joint work in project teams. Unfortunately, we did not have the data to test this claim.

Model 5 tests whether experience has an effect on activity and popularity. Activity is an effect that tests the number of outgoing ties that a certain node establishes, while popularity shows the number of incoming ties. The more active a certain node is in the learning network, the more he/she learns from others, and the more popular a certain person is, the more others learn from him/her. As hypothesized, there is a positive effect of experience on popularity, however, the willingness to learn does not seem to diminish as one gains more and more experience. Interestingly, after including the activity and popularity effects of seniority in Model 6, the effect of experience becomes non-significant. Seniority appears to be a more important determinant of popularity than tenure. In other words, people learnt from those higher in the hierarchy (who were also more experienced). This is important evidence of the overlap of formal and informal organizational hierarchy and a positive sign for every learning environment. Where there a misfit between the two, tensions and conflict, as well as power struggles, are likely.

Besides the effects included in the previous models, the final model adds similarity effects in order to check for the presence of homophily. All of the tested similarity effects – gender, tenure, and seniority – have strong and positive effects on the probability of a tie being present. A precondition for a learning relationship to occur is that both people have something in common. In this research the evidence showed that people of the same gender, of similar experience (tenure), and of the same hierarchical level (seniority) are more likely to form a learning relationship than would be expected on average. To sum up: (1) learning networks are characterized by clustering; (2) belonging to the same location and/or department creates opportunities for learning relationships to form; (3) people higher on the hierarchical ladder as well as more experienced are also more sought after for learning; (4) gender, tenure, and hierarchical level are all sources of homophily, which is highly evident in learning relationships.

Discussion and future challenges

The social network analysis of a learning network within this software company provided support for the learning network perspective. Learning needs to be seen as both participation in a community of practice and a flow of previously acquired knowledge. Evidence for both sides of the coin was found in this case. On the one hand, learning often occurs in project settings and mainly involves the transfer of tacit knowledge through

participation. On the other, those employees who are most often seen as a source of learning are those with above average tenure within the company and hence above average accumulated experience and knowledge. Hence, we believe that this study has provided some initial indications that the learning network perspective can combine the previously disparate acquisition and participation perspectives on organizational learning. The learning network observed seems to be a horizontal one, with an egalitarian organizational structure, organically oriented learning processes, and an open content structure.

When assessing those effects governing the structure of the learning network it is evident that network learning occurs mostly in cliques, as confirmed both through the presence of brokers in the descriptive network analysis and the analysis of the in-2-stars effect. Members of the learning network form clusters in which learning is much more intense than with other parts of the network. People need an opportunity for learning to occur. This means that if you are in the same location or belong to the same department as your co-worker it is more probable that you will learn from them. Despite the fact that a horizontal learning network has been analyzed, seniority (e.g. hierarchical position) appears to be a more important determinant of popularity than tenure (experience). Nevertheless, actors would like to learn from those who are superior to them on the hierarchical ladder, as well as from those who have more experience (measured in terms of tenure within the company). We expect that if we had collected data on tenure within the industry (not only within the company) we would have seen evidence of an even stronger popularity effect of experience. This remains a challenge for future research.

There are several implications of our research. From a theoretical perspective we have shown that the network perspective complements previous perspectives by merging the acquisition and participation perspectives on organizational learning. It deepens the understanding of learning processes within organizations by observing learning networks at multiple levels of research (actor, dyadic, triadic, sub-network, and global network levels). Hence, we believe it offers a useful framework for studies of learning networks in other contexts. Future studies will need to examine another trait of learning environments, i.e. the inter-organizational level of organizational learning networks. From a practice-oriented perspective social network analysis applied in a learning context can provide a strong management tool for identifying and rewarding central employees in an organization, for developing a fit between formal and informal organizational structures (Krackhardt & Hanson, 1993), for supporting a reorganization of the reward system, for helping an understanding of the organizational culture within the company (Cross & Prusak, 2002), for helping organize education and training programs, for supporting collaboration (Cross, Borgatti, & Parker, 2002), etc. On the other hand, such a tool needs to be handled with the utmost care, since it can very easily be misused. Nevertheless, the managerial implications of our research show that managers need to create opportunities for people to learn by co-locating them, by forming project teams with heterogeneous knowledge and enough similarities such that learning networks will actually be established. Knowledge-intensive organizations also need to devote attention to their mentoring systems. Mentors are expected to be drafted from amongst senior and experienced organizational members. Again, both the mentor and his prodigies need to have something in common. Balancing all those aspects and patterns of learning networks will have a positive impact on the intra-organizational learning and consequently contribute to organizational performance.

Future work in the area will need to apply the learning network in other settings – profit and non-profit organizations and institutions. Valuable insights with regard to supporting or rejecting the learning network perspective would emerge after conducting a

similar analysis in companies and organizations of various sizes, different industries, other countries, etc. Expanding the empirical research would contribute in terms of the breadth of possible generalizations. The authors acknowledge that these results apply more to knowledge-based organizations in a specific setting and that in order to generalize the implications further research work is needed. In addition, the further development of the learning network perspective is needed in order to allow for the embeddedness of learning ties within strong co-worker and friendship ties, as is evident from the multiplex analyses of advice ties present in the literature (Lazega & Pattison, 1999). Observing intra-organizational learning networks over time is another possible direction for future research, which would help in an understanding of the dynamic evolution of learning phenomena.

Notes

1. A dyad is a combination of two actors in the graph. For instance, the presence of a tie is a property of a dyad.
2. For example reciprocity, which is the tendency to reciprocate the relation (if I learn from you, you learn from me too).

Notes on contributor

Miha Škerlavaj is an assistant professor of management and organization at the University of Ljubljana, Faculty of Economics, Department for Management and Organization, where he teaches courses on management, organizing and decision-making, and business research methods. His research interests include knowledge and learning networks, impact of organizational learning and information technologies on performance, and learning organization. He has published in *Journal of American Society of Information Systems and Technology*, *International Journal of Production Economics*, *Expert Systems with Applications*, etc. He holds a PhD from the University of Ljubljana for his dissertation 'The Network Perspective and Performance of Organizational Learning: Theoretical and Empirical Analysis'. More information is available at: <http://www.mihaskerlavaj.net>.

Vlado Dimovski is a full professor of management and organizational theory at the University of Ljubljana, Faculty of Economics in Slovenia. He holds B.A. degrees in Economics and Philosophy, M.A. in Economics, and Ph.D. in Management and Finance. As an academician Dimovski has taught and researched at various universities and institutions, and has published numerous articles in recognized journals. His bibliography is available at: <http://splet02.izum.si/cobiss/bibliography?langbib=eng&li=en&code=08627>. His academic research interests cover learning organization, competitiveness, corporate strategy, developing knowledge-based organizations, and labor markets. Besides his university position, professor Dimovski was the State Secretary for Industry (1995–97), the president of the Center for International Competitiveness (1997–2005), and Minister for Labor, Family and Social Affairs (2000–2004).

Andrej Mrvar, (Ph.D. in Computer Science at Faculty of Computer and Information Science, University of Ljubljana) is Associate Professor of Social Science Informatics at the Faculty of Social Sciences. He has won several awards for graph drawings at competitions between 1995 and 2005. Since 2000 he has edited the statistical journal *Metodoloski zvezki – Advances in Methodology and Statistics*. He is one of the co-authors of the programme package Pajek (with Vladimir Batagelj) and one of the co-authors of the book *Exploratory Social Network Analysis with Pajek* (Cambridge University Press, 2005).

Marko Pahor defended his Ph.D. thesis in 2003 at the University of Ljubljana, Slovenia, after spending a year as a Marie Curie fellow in Groningen, Netherlands. He is now working as an assistant professor and head of the new Bologna type Ph.D. study at the Faculty of Economics, Ljubljana. His main research interest lies in applications of social networks and their evolution in different business and economics settings. He collaborates in several national and also international projects.

References

- Andrews, P.H., & Herschel, R.T. (1996). *Organizational communication – Empowerment in a technological society*. Boston, MA: Houghton Mifflin.
- Argyris, C., & Schön, D.A. (1996). *Organizational learning II – Theory, method, and practice*. Reading, MA: Addison Wesley.
- Bapuji, H., & Crossan, M. (2004). From questions to answers: Reviewing organizational learning research. *Management Learning*, 35, 397–417.
- Batagelj, V., & Mrvar, A. (1996). *Pajek – Program for large network analysis*. Retrieved January 6, 2007, from <http://vlado.fmf.uni-lj.si/pub/networks/pajek>
- Batagelj, V., & Mrvar, A. (1998). Pajek: A program for large network analysis. *Connections*, 21, 47–57.
- Birkinshaw, J., & Hagström, P. (2002). *The flexible firm – Capability management in network organizations*. Oxford, UK: Oxford University Press.
- Bloch, S., & Bates, T. (1995). *Employability*. London: Kogan Page.
- Boer, P., Huisman, P., Sniijders, T.A.B., & Zeggelink, E.P.H. (2001). *StOCNET: An open software system for the advanced statistical analysis of social networks*. Retrieved March 7, 2007, from <http://stat.gamma.rug.nl/stocnet>
- Brass, D.J. (1985). Men's and women's networks: A study of interaction patterns and influence in organizations. *Academy of Management Journal*, 28, 327–343.
- Brass, D.J. (1995). A social network perspective on human resources management. *Research in Personnel and Human Resource Management*, 13, 39–79.
- Cook, S.D.N., & Brown, J.S. (1999). Bridging epistemologies: The generative dance between organizational knowledge and organizational knowing. *Organization Science*, 10, 381–400.
- Cross, R., Borgatti, S., & Parker, A. (2002). Making invisible work visible: Using social network analysis to support strategic collaboration. *California Management Review*, 44, 1–22.
- Cross, R., Parker, A., Prusak, L., & Borgatti, S.P. (2001). Knowing what we know – Supporting knowledge creation and sharing in social networks. *Organizational Dynamics*, 30, 100–120.
- Cross, R., & Prusak, L. (2002). The people who make organizations go – or stop. *Harvard Business Review*, 80, 104–112.
- Cyert, R.M., & March, J.G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice Hall.
- De Geus, A.P. (1988). Planning as learning. *Harvard Business Review*, 88, 70–74.
- de Nooy, W., Mrvar, A., & Batagelj, V. (2005). *Exploratory social network analysis with Pajek*. New York: Cambridge University Press.
- Doreian, P., Batagelj, V., & Ferligoj, A. (2005). *Generalized blockmodeling*. Cambridge, UK: Cambridge University Press.
- Easterby-Smith, M., Crossan, M., & Nicolini, D. (2000). Organizational learning: Debates past, present and future. *Journal of Management Studies*, 37, 783–796.
- Easton, G. (1992). Industrial network – A review. In B. Axelsson & G. Easton (Eds.), *Industrial networks – A new view of reality*. London: Routledge.
- Elkjaer, B. (2004). Organizational learning – The third way. *Management Learning*, 35, 419–434.
- Filipczak, B. (1995). You're on your own: Training, employability, and the new employment contract. *Training*, 32, 29–37.
- Hager, P. (2004). Conceptions of learning and understanding learning at work. *Studies in Continuing Education*, 26, 3–17.
- Huber, G.P. (1991). Organizational learning: The contributing process and the literatures. *Organization Science*, 2, 88–115.
- Ibarra, H. (1992). Homophily and differential returns: Sex differences in network structure in an advertising firm. *Administrative Science Quarterly*, 37, 422–447.
- Ibarra, H. (1993). Personal networks of women and minorities in management: A conceptual framework. *Academy of Management Review*, 18, 56–87.
- Krackhardt, D., & Hanson, J. (1993). Informal networks: The company behind the chart. *Harvard Business Review*, 71, 104–111.
- Lave, J., & Wenger, E. (1991). *Situated learning – Legitimate peripheral participation*. Cambridge, UK: Cambridge University Press.
- Lazega, E. (1992). *The micropolitics of knowledge*. New York: A. de Gruyter.
- Lazega, E. (2001). *The collegial phenomenon: The social mechanisms of cooperation among peers in a corporate law partnership*. Oxford, UK: Oxford University Press.

- Lazega, E., & Pattison, P.E. (1999). Multiplexity, generalized exchange and cooperation in organizations: A case study. *Social Networks*, 21, 67–90.
- March, J., & Simon, H.A. (1958). *Organizations*. New York: Wiley.
- McPherson, J.M., & Smith-Lovin, L. (1987). Homophily in voluntary organizations. *American Society Review*, 52, 370–379.
- McPherson, J.M., Smith-Lovin, L., & Cook, J.M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27, 417–444.
- Mitchell, J.C. (1969). The concept and use of social networks. In J.C. Mitchell (Ed.), *Social networks in urban situations*. Manchester, UK: University of Manchester Press.
- Monge, P.R., & Contractor, N.S. (2003). *Theories of communication networks*. Oxford, UK: Oxford University Press.
- Nicolini, D., Gherardi, S., & Yanow, D. (2003). *Knowing in organizations – A practice-based approach*. Armonk, NY: M.E. Sharpe.
- Pahor, M., Škerlavaj, M., & Dimovski, V. (2008). Evidence supporting the network perspective on organizational learning. *Journal of the American Society for Information Science and Technology*, forthcoming.
- Pedler, M., & Aspinwall, K. (1998). *A concise guide to the learning organization*. London: Lemos & Crane.
- Poell, R.F., Chivers, G.E., Van der Krogt, F.J., & Wildermeersch, D.A. (2000). Learning-network theory – Organizing the dynamic relationships between learning and work. *Management Learning*, 31, 25–49.
- Robins, G.L., Snijders, T.A.B., Wang, P., Handcock, M., & Pattison, P. (2007). Recent developments in exponential random graph (p*) models for social networks. *Social Networks*, 29, 192–215.
- Senge, P.M. (1990). *The fifth discipline – The art and practice of the learning organization*. New York: Doubleday Currency.
- Snijders, T.A.B. (2001). The statistical evaluation of social network dynamics. In M.E. Sobel & M.P. Becker (Eds.), *Sociological methodology* (361–395). Boston: Basil Blackwell.
- Snijders, T.A.B. (2002). The Markov chain Monte Carlo estimation of the exponential random graph model. *Journal of Social Structure*, 3, 2–40.
- Snijders, T.A.B., & Huisman, M. (2002). *Manual for SIENA version 1.95*. Retrieved February 14, 2007, from <http://stat.gamma.rug.nl/snijders/socnet.htm>
- Snijders, T.A.B., Pattison, P.E., Robins, G.L., & Handcock, M.S. (2006). New specifications for exponential random graph models. *Sociological Methodology*, 36, 95–153.
- Škerlavaj, M., Indihar Štemberger, M., Škrinjar, R., & Dimovski, V. (2007). Organizational learning culture – The missing link between business process change and organizational performance. *International Journal of Production Economics*, 106, 346–367.
- Tichy, N.M., Tushman, M.L., & Fombrun, C. (1979). Social network analysis for organizations. *Academy of Management Review*, 4, 507–519.
- Van der Krogt, F.J. (1998). Learning network theory – The tension between learning systems and work systems in organizations. *Human Resource Development Quarterly*, 9, 157–177.
- Wasserman, S., & Faust, K. (1994). *Social network analysis*. Cambridge, UK: Cambridge University Press.
- Wasserman, S., & Pattison, P. (1996). Logit models and logistic regressions for social networks 1. An introduction to Markov graphs and p*. *Psychometrika*, 61, 401–425.
- Wilson, A.L., & Cervero, R.M. (1997). The song remains the same: The selective tradition of technical rationality in adult education programme planning theory. *International Journal of Lifelong Education*, 16, 84–108.

Appendix 1. Number of connections within and among various groups

Table A1. Geographical location.

	Ljubljana	Belgrade	Zagreb
Ljubljana	236	2	2
Belgrade	6	23	0
Zagreb	5	0	30

Table A2. Business units.

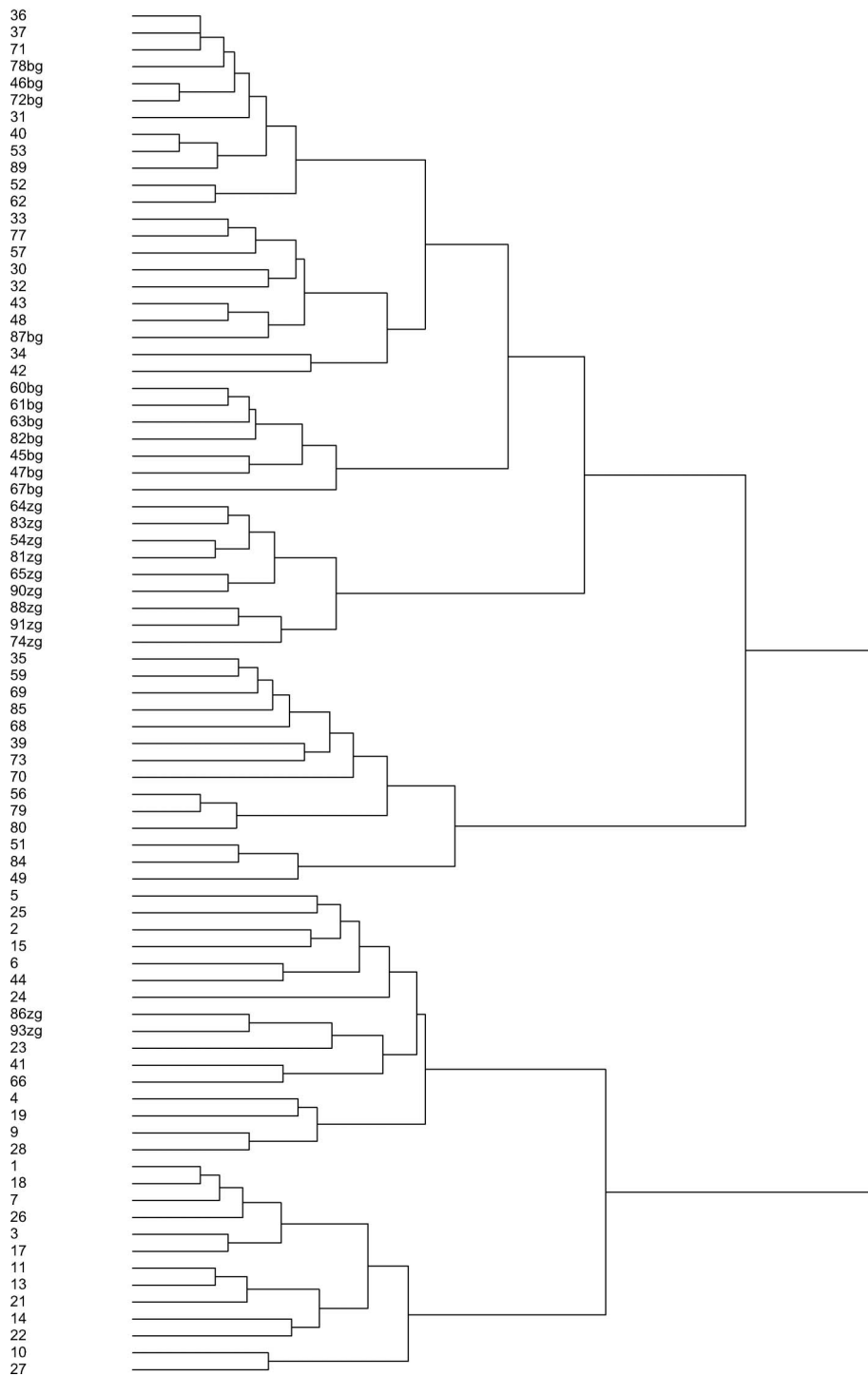
	ERP Solutions	Industry Solutions	Banking Solutions	Others
ERP Solutions	127	30	0	2
Industry Solutions	22	16	1	7
Banking Solutions	6	9	38	12
Others	0	9	2	23

Table A3. Hierarchical position.

	Top management	Middle management	Line management	Project management	Personnel
Top management	91	48	17	10	14
Middle management	24	14	16	0	4
Line management	4	7	7	0	8
Project management	7	7	3	2	3
Personnel	3	0	3	3	9

Appendix 2: Dendrogram (Ward's method on corrected Euclidian distance)

Pajek - Ward [0.00,15.57]



Appendix 3. Model specification

We have a digraph of g actors represented by an adjacency matrix

$$Y = y(i, j), \quad 1 \leq i, j \leq g$$

where $y_{ij} = 1$ or 0 indicates that there is or there is not a tie between actors i and j .

In order to establish which mechanisms govern the learning network, the authors decided to model the network using the exponential random graph model (Snijders, 2001), also known as the p^* model (Wasserman & Pattison, 1996). p^* is a family of probability functions in the form

$$P_{\theta}\{Y = y\} = \exp[\theta' u(y) - \psi[\theta]] \tag{1}$$

where Y is the adjacency matrix of a digraph, the sufficient statistic $u(y)$ is any vector of statistics of the digraph and θ is the vector of the parameter being estimated. The model basically assesses the probability of the existence of a tie between two actors given the network properties, the properties of each actor, and the properties of the dyads. One can rewrite equation taking into account the division of effects in three groups in the following way

$$P_{\theta}\{Y = y\} = \exp[\theta'_N u_N(y) + \theta'_A u_A(y) + \theta D'_N u_D(y) - \psi[\theta]] \tag{2}$$

$u_N(y)$ is a vector of statistics describing network or structural properties, $u_A(y)$ is a vector of statistics reflecting actor properties, and $u_D(y)$ is a vector of statistics reflecting the properties of the dyad. θ values are vectors of the corresponding parameters.

A common network statistic is reciprocity, reflecting the tendency to return the tie

$$u(y) = \sum_{i < j} y_{ij} \cdot y_{ji} \tag{3}$$

A large group of network properties falls within the definition of n -stars (n being 2, 3, . . .) and show the tendency of actors to have more than one relation. For example, an out-2-star is defined as:

$$u(y) = 1/2 \sum_{i, j, h=1, j \neq h}^g y_{ij} \cdot y_{ih} \tag{4}$$

In the initial runs of the model we had problems achieving model convergence. After consulting the literature (Robins, Snijders, Wang, Handcock, & Pattison, 2007) we decided to include some new specifications of parameters for the exponential random graph model, namely the alternating k -stars and alternating triangles. For example, the alternating in- k -stars are defined as:

$$u(y) = c^2 \sum_{i=1}^n \{(1 - 1/c)^{x_{+i}} + (x_{+i}/c - 1)\} \tag{5}$$

where c is a specified parameter. The alternating stars and triangles account for the variability in the in- and out-degrees of actors and help the model to become convergent. (Snijders et al., 2006).

There are three basic covariate-related effects for each covariate V :

- covariate-related popularity, defined by the sum of the covariate over all those actors to whom actor i has a tie. It expresses the effect a certain property of an actor has on the number of inbound ties

$$u(y) = \sum_j y_{ij} \cdot v_j \tag{6}$$

- covariate-related activity, denoted by the out-degree of i weighted by its covariate value. It expresses the effect a certain property of an actor has on the number of outbound ties

$$u(y) = v_i \sum_j y_{ij} \quad (7)$$

- covariate-related dissimilarity, denoted by the sum of covariate differences between i and the others to whom he is related. It shows how differences between actors affect the probability of the existence of ties between them

$$u(y) = \sum_j y_{ij} |v_i - v_j| \quad (8)$$

Positive covariate-related popularity or activity effects will lead to associations between the covariate and the in-degrees and out-degrees, respectively. A negative covariate-related dissimilarity effect will lead to relations being formed, especially between actors with similar values on the covariate.

The third set of effects explored encompasses the dyadic covariate effects. This effect enters the model mainly in the form of covariate-related preference, defined by the sum of the values of another relation, w_{ij} , for all others to whom i is related

$$u(y) = \sum_j y_{ij} \cdot w_{ij} \quad (9)$$

To rephrase this, we test whether a tie of another type which exists between two actors in the network has an effect on the tie in our dependent relation.