Representation of Tacit Knowledge In Organizations

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Abstract

In this study, we report methods and some results concerned with explicating the nature of knowledge in an organization of industrial trainers who are at different levels in expertise. Working with the three experts in the center, we defined a list of 29 core elements to be acquired and mastered in the career paths of the professional trainers in the center. The rating task presented employees with all possible pairs of elements and required them to judge the relatedness of the elements using a 10-point scale(0, 1, 2, …, 9). Twenty one subjects completed the ratings. The rating task assumes that the less related elements be perceived further apart in one's knowledge structure. The ratings were put into a procedure called Pathfinder(Schvaneveldt, Durso, & Dearholt, 1985), a network scaling program based on the graph theory in mathematics. It generates a link-weighted network, a configuration in which elements are depicted as nodes and relationships are depicted as links between nodes. We used a method of assessing knowledge structure in order to obtain access to participants'' tacit, abstract representations and worked with a small group of experts to indentify the detailed level-specific facts and to understand the differentiation among the groups.

One of the most basic and long standing issues in studies of organizational knowledge is the problem of knowledge elicitation and representation. How do we assess and represent the knowledge structure of novices vs experts? Knowledge assessment and representation, as carried out in organizations, appears as a relatively simple matter. They assess knowledge by simply asking factual questions and represent individual's knowledge by presenting the individual's score in terms of relative standing in comparison with others.

in this conventional approach assessment comes first and representation comes later, which is adequate in dealing with declarative knowledge. The representation of knowledge in organizations is usually in terms of education or training years, academic degree, certificate, or some unidimensional scales. These representations are in terms of attributes and may be perfectly adequate for representing certain types of knowledge(e.g.: declarative knowledge) where the relationship among the knowledge elements are not particularly relevant. At this level of knowledge representation, the "facts" in the learning domain can be independent and additive(Goldsmith & Johnson, 1990).

However, representation becomes more fundamental when we have to deal with tacit knowledge or automatized skills. It is because the frames regarding the representation or organization of knowledge have strong implications for how we assess knowledge(Goldsmith & Johnson, 1990). In this study, we are more interested in relatedness of knowledge where relationships or organization of the elements are relevant. For this type of study, we need to represent the "configural" property of knowledge and assess the configuration in the representation. Attributes data may be very convenient in determining the relative stance of organization members, but it tells us very little regarding the depth and width of knowledge that the members have. We are going to apply the assumption in cognitive psychology to capture the representation of knowledge and assess its quality. Cognitive psychologists(e.g.: Bower, 1972) assume that knowledge exists in the form of interrelationships among elements and knowledge organization can best be captured with the representation of its structure. It is our aim to develop structural representation and assess this configural property of the knowledge that members in an organization have. Especially we hope to be able to capture the property of tacit knowledge.

Tacit Knowledge and Its Measurement

Tacit Knowledge

Experts' knowledge or expertise is powerful because of its "abstracted" character, which makes it the hardest to capture(Means & Gott, 1988). It is very hard to duplicate the abstracted character, making expertise as an important part of the core competence of an organization. The abstract memory stores of experts are used to represent and solve novel problems. It would be beneficial if one could capture and teach them for others in the organization. Given the context of a specific problem, experts can readily retrieve the stored knowledge and solve the problem. However, they are much less able to provide explicit rules defining the context in which a given problem representation, strategy, or some other knowledge will be evoked. The expert is often unaware of the abstract principles that are acquired out of practical experience.

A review of the definitions of tacit knowledge should be in order as in table 1.

Table 1. Definitions of Tacit Knowledge

Polanyi(1958): Knowledge which sources and contents do not belong to routine consciousness. It is personal, context-specific, hard to formalize and communicate
Hayek(1945; 1962): deep rules maintained in the supraconscious that are not available by routine conscious examination
Sternberg, Wagner, Williams, & Horvath(1995): procedural in nature and action-oriented knowledge, acquired without direct help from others
Nonaka & Takeuchi(1995): knowledge of experience(tacit, physical, subjective), simultaneous knowledge(created "here and now" in specific practical context), analog knowledge, knowledge that is relevant to the attainment of goals people value

The definitions of Polanyi(1958) and Hayek(1945; 1962) are more philosophical. Sternberg et al.'s(1995) definition is more about the implicit acquisition process without direct help from others. However, tacit knowledge can be obtained by help from others as shown in Anderson's(1983) model, where declarative knowledge is refined through an explicit process of compilation and practice, changes to procedural knowledge, and finally is internalized to become strategic knowledge. Nonaka and colleagues(Nonaka, 1994; Hedlund & Nonaka, 1994) recognized the importance of Anderson's model in explaining one of their knowledge creation processes: transforming explicit knowledge to tacit knowledge through an explicit learning(teaching) process. The framework of acquiring tacit knowledge through an implicit/explicit learning process has been the basis in the literature of knowledge management(e.g., Nonaka, 1994; Nonaka &

Takeuchi, 1995).

In this study, tacit knowledge will be defined as knowledge that is practical context-specific in the process of creation, procedural in nature, routinized(automatized) in the level of mastery, and hard to formalize and communicate in accessibility by routine consciousness.

Access and Measurement of Tacit Knowledge

What we expect organizational members to learn is tacit knowledge that is difficult, if not impossible, to retrieve readily. To the extent that some relevant knowledge(e.g.: procedural knowledge) is tacit, the knowledge should be approached from structural representation and assessment of abstract or conceptual aspects of knowledge. We are going to use an approach that requires minimal retrieval demands, and represents members' knowledge organization of a specific domain.

Although there are numerous strategies for measuring knowledge structure as in Flanagan(1990), structural assessment is recently used often(e.g.: Goldsmith & Johnson, 1990; Goldsmith, Johnson, & Acton, 1991). In this method, judgments of similarity or closeness among a previously defined set of core elements are required. Elements are then mapped by submitting the judgements data to a scaling algorithm.

To be knowledgeable of a domain requires that the important elements are interrelated and organized in a desirable configuration. The resulting map is assessed by examining its similarity to a map of expert(s) or to a prototype or by evaluating its level of complexity(Kraiger, Ford, & Salas, 1993). The tool for creating structural representation is a network scaling, an application of graph theory in mathematics.

Graph theory in mathematics(e.g.: Aho, Hopcrofit, & Ullman, 1974; Christofides, 1975) is the basic foundation in the study of networks. A network is defined as a set of nodes representing entities and links between nodes. Depending on the form of proximity matrix of nodes, links may be directed(one-way) or undirected(two-way). Some sources of proximity matrix include: (a) similarity/dissimilarity judgments of psychological proximity; (b) incidence of confusions between pairs of entities; (c) free- or controlled- association norms; (d) incidence of co-occurrence; (e) counts of common features; or (f) physical distance(Schvaneveldt, Durso, & Dearholt, 1985). With a symmetric matrix, undirected networks are generated. With an asymmetric matrix, directed networks are generated. Each link in the networks produced by a network scaling algorithm has a weight indicating the distance associated with the link. A path in a network consists of a sequence of nodes and connecting links. Although there may or may not be directly connecting links between nodes, paths provide for connections for any two nodes in a network. The length of a path is determined as a function of the weights associated with the links in the path. Network scaling algorithm employeed in this study is Pathfinder(Schvaneveldt, Durso, Dearholt, 1985). Pathfinder produces estimates of all of the pairwise distance between nodes to be mapped on networks.

With the same number of nodes we can draw a lot of different networks. The objective of employing network scaling method is to define a parsimonious network that includes important links, resulting a network of the shortest possible paths between nodes given the set of distance estimates.

Algorithm of Pathfinder

A link is included in the Pathfinder solution if and only if the link is a minimum-length path between the pair of nodes connected by the link. A path between two nodes may consist of any number of links. The length of a path is a function of the distances associated with the links in the path.

A general function defining the path length allows Pathfinder to create a family of networks including minimally connected(MIN) network and maximally connected(MAX) network. The general function comes from the Minkowski r-metric originally developed as a generalized distance measure in multidimensional space. The r-metric defines a general measure of distance in a space of N dimensions.

$$D = [d_1^r + . . . + d_i^r + \cdots + d_N^r]^{(1/r)} \qquad 1 \le r \le \infty \quad . . . . . (1)$$

This expression can also be applied to defining the length of a path in a network. Let d_i be the distance associated with link i in a path. The set of all distances in a path with N links is given by d_i in eq. (1). Then, the length of the path is given by D in eq. (1).

For any two values of r, the network defined by the smaller value will include all the links in the network defined by the larger value. Pathfinder generates a unique network structure only for r=∞ when the MIN network is generated. When the measurement level is ordinal as is usual in behavioral or social sciences, r=∞ provides the only unique structure. If one were confident in the level of measurement(e.g.: higher than ordinal level), one could try other values of r(Schvaneveldt, Durso, & Dearholt, 1985).

Another parameter used by Pathfinder is q, the maximum number of links in a path. With n nodes to be scaled, q can be from 2 to n-1. Just as the complexity of networks decreases with increasing r, complexity also decreases with increasing q. With the two parameters r and q, a particular network can be identified.

We are particularly interested in a network of (r=∞, q=n-1). This network is always the most parsimonious, because the length of a path is the distance value of the longest link along the path(this is called the dominant metric). And for a graph having n nodes the maximum number of links along the path without a cycle is n-1.

Method

We turn next to an empirical study that attempted to represent and assess empirically derived knowledge structure. The basic purpose of the study was to investigate the differential features of knowledge structures and progress of domain knowledge. We hypothesized that groups whose structure more closely matches the role model's in the organization will indeed be more knowledgeable and evaluated highly by their supervisors. Relatedness of knowledge structure was measured by the set-theoretic index C which is developed and validated by Goldsmith and Johnson(1990). Goldsmith and Johnson showed that their index C was more predictive of performance than other indices not based on configural information.

Goldsmith, Johnson, & Acton(1991) evaluated the validity of the Pathfinder scaling algorithm to assess students' cognitive representation of classroom learning. Judgements data of students and the instructor were submitted to Pathfinder to create knowledge. The similarity between each student's and the instructor's networks was assessed using a set-theoretic measure C. The correlation between exam performance over the course of the semester and C was .74($p<.01$), which means C a good predictor. In Kraiger and Salas(1992, recited from Kraiger, Ford, & Salas, 1993), the network similarity index C between trainees' and training experts' were correlated with the traditional measure of knowledge for the trainees(Navy pilots).

Domain

The knowledge domain was knowledge and skills of the trainers in a training center of a large business group in Korea. We will call this group "Group" from now on. The primary role of the trainers was to analyze the knowledge and skills of workers in the subsidiaries of the Group and train them to upgrade their capacity. The trainers completed initial training and had at least five months of on-the-job training from their supervisors.

We selected an initial set of knowledge elements considered to be central to the job of trainers with the help of three experts in the center and then obtained suggestions from other managers who run the center and worked as trainers before they were promoted, resulting in a revised set of 29 elements. The final set of elements is provided in the table 2.

Table 2. The Final Set of Knowledge Elements

category	knowledge elements	short-form that will be used in the network
1.Understanding the Group	(1) Group Vision	G-V
	(2) Group History	G-H
	(3) Group Culture	G-CUL
2.Understanding the Training Center	(4) Vision of the Center	VIS
	(5) Roadmap of the Center	RDMAP
	(6) History of the Center	HST
	(7) Culture of the Center	CUL
	(8) Structure and Operation of the center	ST-OP
3.Understanding Industrial Training	(9) Characteristics of Adult Learning	ADLT-L
	(10) Meaning and Role of Industrial Training	MR-ITR
	(11) Role of HRD Personnel	R-HRD
	(12)Decision-Making	DM
	(13)Communication	COM
	(14)Work-related Feedback	FD
	(15) Creativity	CRE
	(16)Customer Service	CS-SRV

4.Curriculum Development	(17)Concept of Educational Technology	CPT-ET
	(18)Model of Instructional Design	MDL-ID
	(19)Theory of Instruction and Learning	I&L
	(20) Method of Curriculum Development	CM-DVL
5.Lecturing	(21) Understanding Facilitation	U-FACL
6.Training Operation	(22)Flow of Training Operation	FLO-I
	(23)Developing Questionnaire	DVL-Q
7.Developing Instructional Media and Use	(24)Use of Instructional Equipment and Material	U-E&M
8.Use of Office Automation System and Documentation	(25) Writing and Use of Documents	W&U_D
	(26)Use of the System and Machines	SYS&M
	(27)Office Etiquette	ETO
9.Knowledge about other Training Centers & Subsidiaries	(28)Training Centers in the Nation or Overseas	T-CTR
	(29) Subsidiaries	SUB

Trainers' performance in the center was measured by the ratings of two supervisors on the nine items of nine-point scale. The nine items are based on the nine categories in the table 2.

Subjects and Procedure

A total 21 ordinary trainers and 3 expert trainers participated in the study. All of the participants have college degrees. The three experts were selected by consulting the general manager of the center and the representation from the average data of these experts served as the role model to which other trainer's representations were compared.

We discuss here the choice of a procedure for collecting proximity data on a set of knowledge elements, particular type of transformations performed on these data, and the methods by which different networks are compared. There are many ways for collecting proximity data: sorting, memory recall tasks, pair comparisons, etc. We used direct judgments of element relatedness as the basis for obtaining knowledge representations. Our choice of relatedness ratings has been also popular in collecting proximity data for multidimensional scaling. Based on the similarity judgments applied to semantic concepts, we expect different levels of knowledge can be interpreted. The advance from novice to expert may be through a continued sequence of analysis and synthesis, resulting a more differentiated and integrated cognitive system.

To begin with, the purpose of the rating project was explained to the participants. They were told they would be rating the relatedness of 406 pairs(n(n-1)/2) of concepts and that these ratings would be used to assess their understanding of their job. Participants were asked to rate the relatedness of each pair of elements using a 10-point scale where 0 corresponded to 'never related' and 9 to 'absolutely related'. At the beginning of the rating session, participants were shown the complete set of elements and were encouraged to start from some pairs that were highly related and go to some that looked quite unrelated. Their age was between 27 and 45(mean=34.5, SD=4.7). Their tenure at the Group was between 1 year and 13 years(mean=7.0 years, SD=4.0 years) and their tenure at the center was between 0.5 year and 6 years(mean=2 years and 7 months, SD=1 year and 11 months).

Participants were instructed to give quick intuitive judgments of relatedness rather than giving a lengthy and deliberate consideration to the pairs. Each participant performed the task individually and at their convenience on the questionnaire. On average, participants took about one hour to complete the set of 406 ratings.

Results

The data from the expert trainers were combined and averaged. We call this data the role model's data or just model's data. We analysed the models' data with those from the ordinary trainers together. The raw data were of similarity among knowledge elements. These similarity data were transformed into dissimilarity by subtracting each rating from 9. Pathfinder networks(r=∞, q=n-1) were derived on the data set individually first to examine the coherence of the proximity data. The coherence of a set of proximity data is a correlation between the original proximity data with the indirect measure of relatedness for each pair of items. The indirect measure is obtained by correlating the proximities between the items and all other items. Very low coherence values(less than .20 or so) is said to mean that ratings were not performed seriously(Schvaneveldt, Durso, & Dearholt, 1985). The coherence of the model's data was .70 which was reasonably high. Examining the coherence index of the 21 ordinary trainers, we found 3 participants show very low coherence values leading us to exclude their data from further analysis. We will present the results from comparing the model's data with the remaining 18 trainers' from now on. Pathfinder representation were obtained for the model and the 18 trainers. The coherence, C index, and performance rated by two supervisors for each trainer are given in table 3.

Table 3. Analysis of 18 Trainer's Data

Participants	Coherence	C index	Performance*
A	.45	.09	4.17
B	.41	.17	5.11
C	.25	.19	4.50
D	.45	.15	4.44
E	.51	.14	6.44
F	.21	.16	4.56
G	.68	.25	5.94
H	.82	.13	5.94
I	.56	.23	5.72
J	.64	.13	5.89
K	.48	.15	6.33
L	.48	.12	6.44
M	.30	.10	5.83
N	.53	.20	7.00
O	.53	.22	6.17
P	.40	.13	7.28
Q	.32	.19	5.50
R	.33	.17	5.11
Mean	.46	.16	5.69
SD	.15	.04	.89

COR(coherence, C)=.20, COR(coherence, performance)=.30,
COR(C, performance)=.48

* performance rating was the mean of the scores that two supervisors rated on a 9 points scale for each participant. Inter-rater reliability was .83.

In table 3, coherence values are above .20. Pearson product-moment correlation between C index and performance rating was .48 which represents that C index is a fine predictor of performance. In the study of Goldsmith and Johnson(1990), this correlation was .74 from 40 participants which was very high. Since we had only 18 participants included in the evaluation, we could have suffered the restriction of range. Agreement of knowledge representation as assessed by C index between each individual and the model are somewhat low.

One way of looking closer at the change of knowledge structure is to categorize the 18 participants into several groups to obtain average of proximity data representing each group. The sets of average data can be analyzed with the data of model together to entertain the parsimony of explanation and improvement of measurement reliability. Based on the values of C index in the table 3, we categorized 18 participants into 5 groups as in table 4.

Table 4. Grouping of the Participants

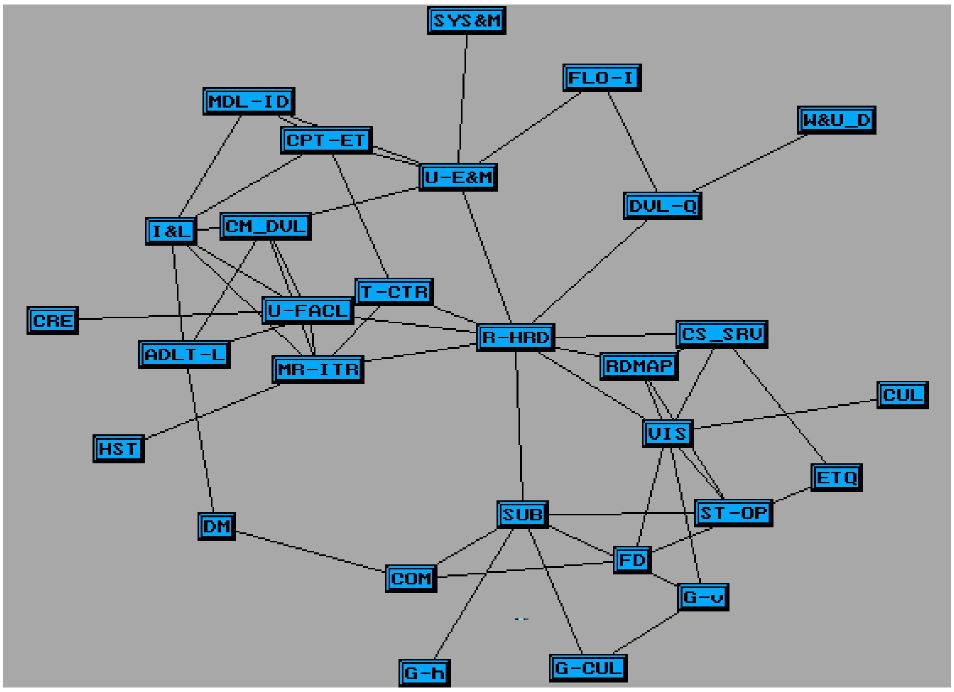
Group	Participants	Coherence	Common links*	C	p-value**
1	G, I, N, O	.72	17	.25	.00
2	B, C, Q, R	.58	17	.22	.00
3	D, E, F, K	.65	13	.17	.00
4	H, J, P	.79	11	.14	.00
5	A, L, M	.56	9	.10	.09

* Number of links that are common in the networks of the group and the "model".

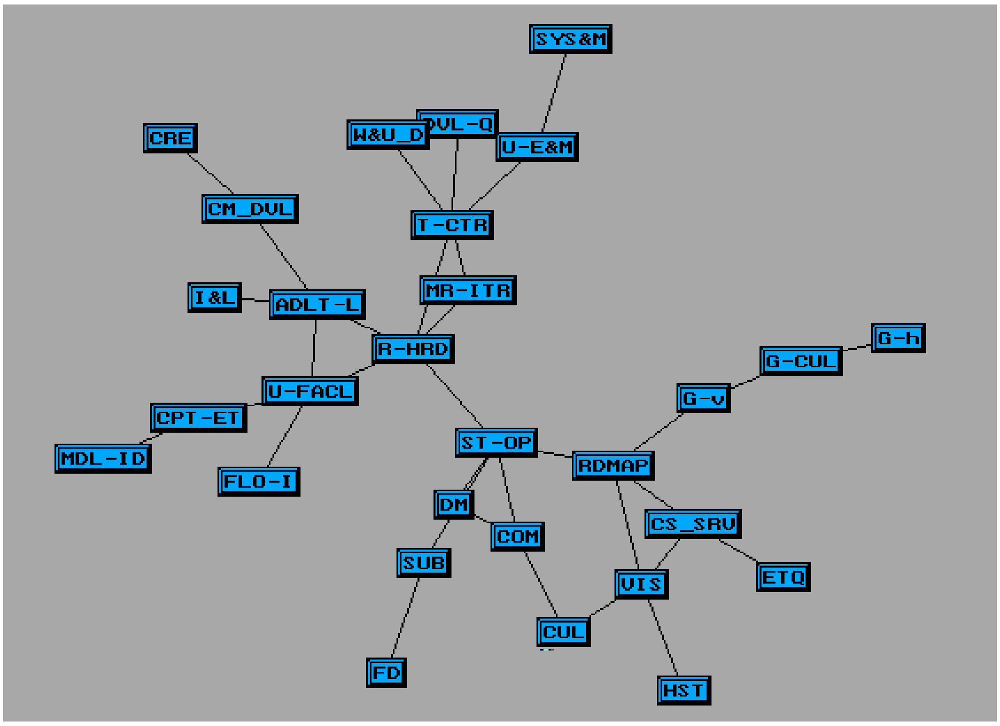
** We present the tail probability from the Pathfinder manual. This p-value is the probability of this large value of C can be observed.

In Figure 1 we present the network of the "model", and those of groups 1 through 5. Based on the meaning of the nodes in the network, we can interpret how knowledge structure changes from the low-skilled group to the model group.

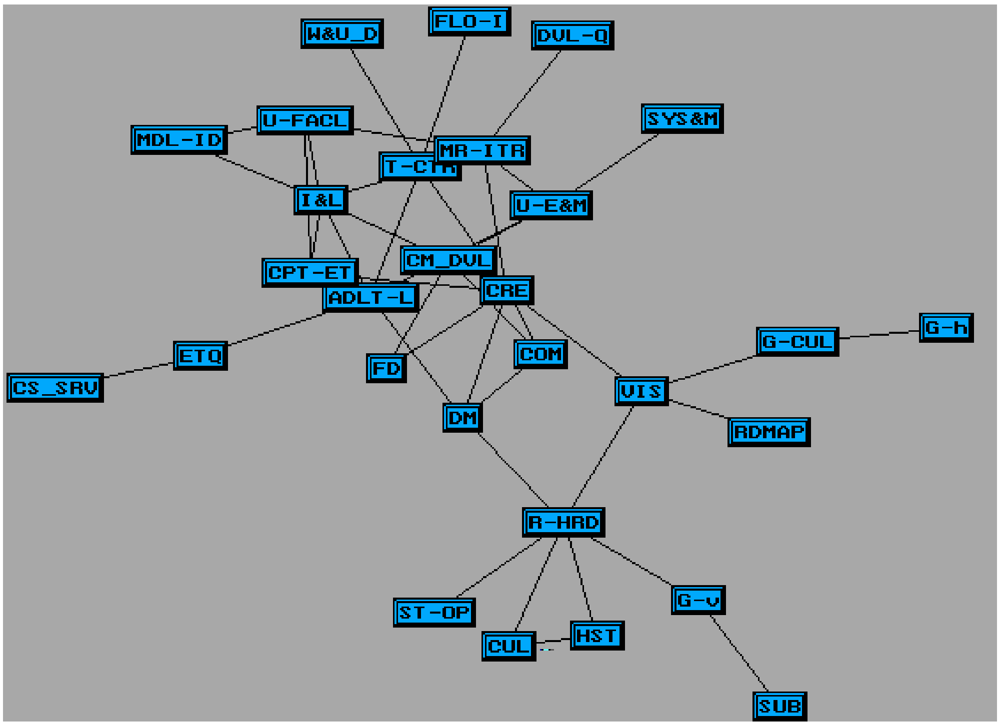
(Model)



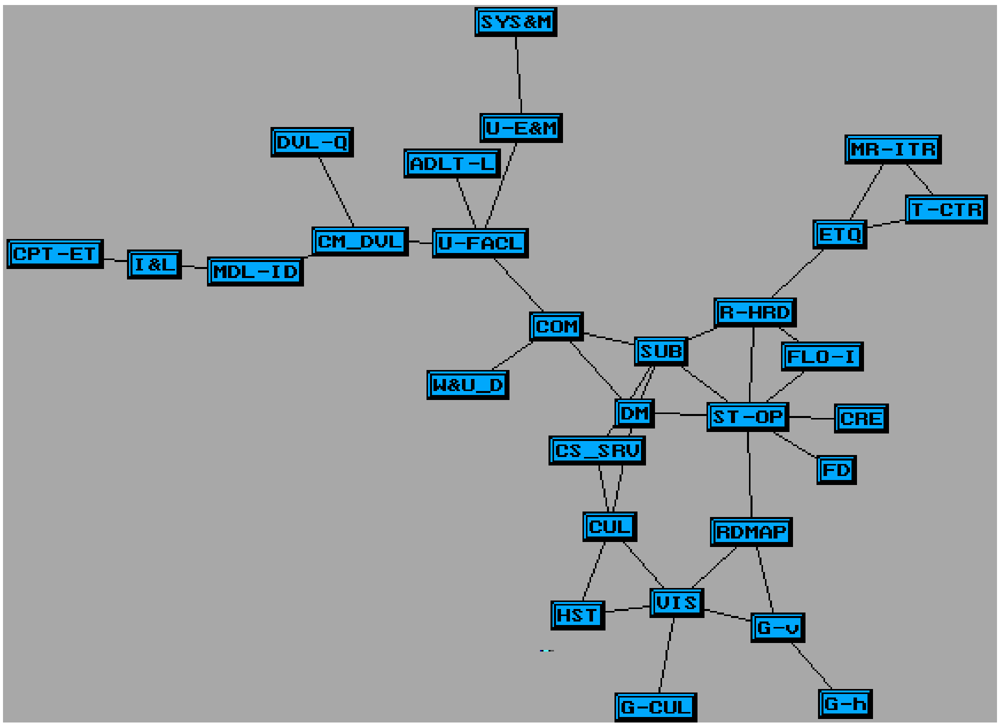
(Group 1)



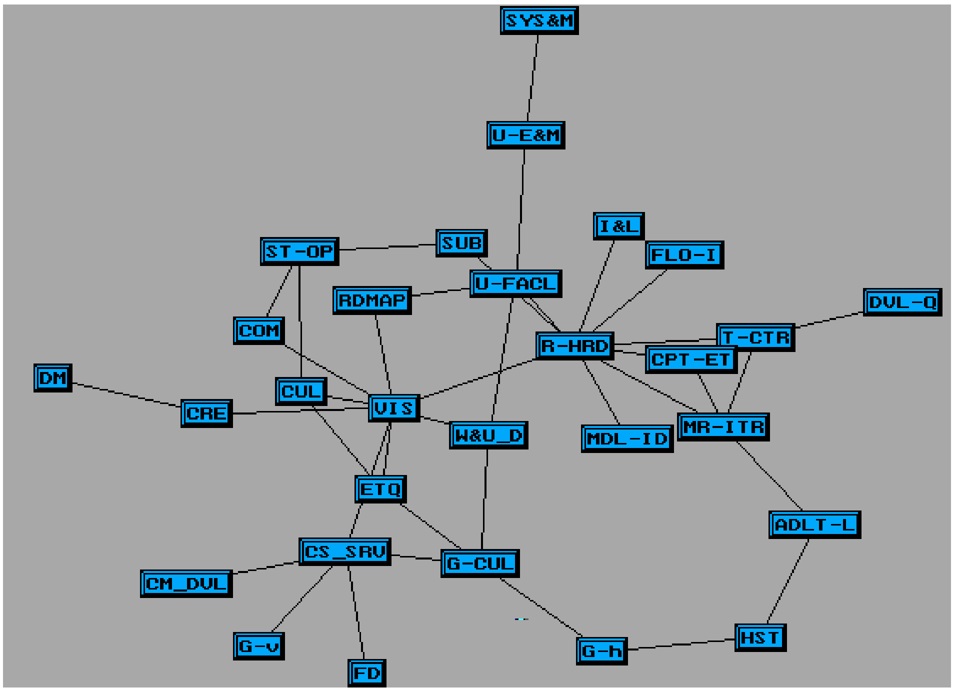
(Group 2)



(Group 3)



(Group 4)



(Group 5)

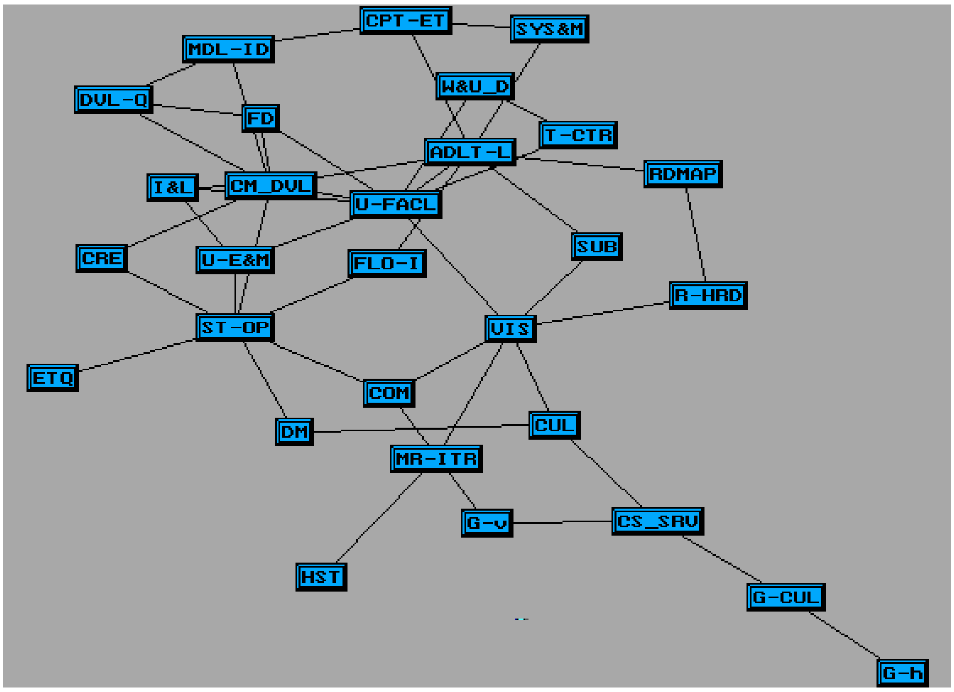


Figure 1. Network Representation of the Model, Groups 1 through 5

We will attempt to assess the configural properties of knowledge structure. But they are not directly obtainable and rather must be interpreted with the help of subject matter experts. For our purposes, we asked the three experts to be involved in our interpretation process.

Interpretation of the Networks

Model

The network of the “model” can be summarized in 3 dimensions: domain-general or –specific; core/secondary knowledge; degree of connection between the general and specific knowledge as shown in Figure 2.

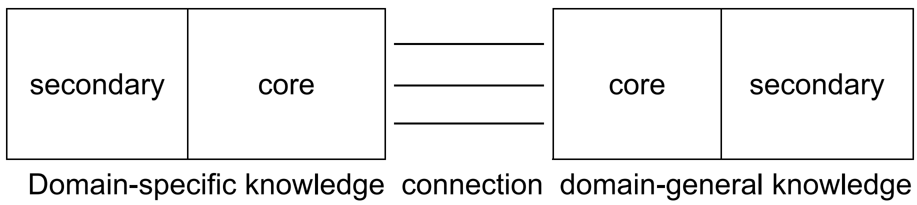


Figure 2. Schema of Knowledge Organization

The right half of the network is about domain-general knowledge such as roadmap, group vision, structure and operation of the center, and knowledge about subsidiaries that serve as environment in operating the training center. The left-half of the network is about domain-specific knowledge that are considered to be the first-handed and core ingredients in generating productivity in the center. This knowledge includes role of HRD personnel, knowledge about other training centers in the nation or overseas, understanding facilitation, curriculum development, concept of education technology, and understanding equipment and materials. As the knowledge elements are located closer to the center and have many links connected to other elements, they are core knowledge in each half of the network. The elements that are located at the far end are secondary knowledge in the sense that they are already well-understood and readily applied without demanding much cognitive resources when they are needed. The connection between the two halves in the network represent that the model experts have good tacit knowledge associating domain-specific knowledge with domain-general knowledge.

As each of the three dimensions gets less identifiable or less clearer, groups 1 through 5 will show different networks that are less or more deviant from the “model” network.

Group 1

The network of group 1 is very similar to that of the model except the knowledge elements in each half are not so densely related as in the model network and the degree of connection between the domain-general and –specific knowledge set is somewhat poor. However, it is clear that group 1 people have a good grasp of organizing the knowledge into two sets and they know what are core or secondary in operation as represented in the hierarchical configuration starting from the R-HRD in the left half and from ST-OP in the right half of the network.

Group 2

Group 2 people seem to have some difficulty in delineating the domain-general and –specific knowledge. They have more emphasis on training- and instruction-related knowledge elements as represented in the dense relatedness among these knowledge elements. Also some of the elements connected to the domain-general knowledge set in the model's network are connected to the training-related knowledge set(e.g.: SC_SRV, ETQ, FD, COM). Although group 2 people are close to group 1 in delineating the knowledge elements into domain-general and –specific set, and representing core/secondary elements, they are not yet as advanced as the group 1.

Group 3

In contrast to the group 2 network where some of the domain-general elements are connected in the domain-specific set, so many of domain-specific knowledge elements are connected to the domain-general set(e.g.: R-HRD, FLO-I, CRE, ETQ, MR-ITR, T-CTR) in the network of group 3. The group 3 is in the middle of classifying the elements into domain-specific and –general sets. In contrast to the emphasis on domain-specific set in the group 2, they have more emphasis on the domain-general set in group 3. It shows that one starts mastery of knowledge from general elements and then turn to specific elements. In the right half of the network, some of the elements(e.g.: SUB, ST-OP, VIS) take central role in the organization of domain-general knowledge set. However the upper-left area representing domain-specific set shows somewhat poor relatedness among the elements.

Group 4

The group 4 is just at the brink of differentiating the two different knowledge sets. However, they do not know which elements take the central role before the differentiation of domain-general and –specific sets is initiated. For example, ST-OP, RDMAP, and SUB take central role in the general knowledge set of group 3 or other higher groups. But they are not yet recognized as such in group 4.

Group 5

The network of group 5 is similar to that of group 4, however, remarkably different from those of other groups and the model. Nothing seems to be organized. RDMAP and R-HRD have been at central positions in other networks, however, they are at peripheral positions here. ST-OP, one of the most central elements in the domain-general set is strongly connected to domain-specific set here. MR-ITR, one of the important elements in the domain-specific set, is in the middle of the domain-general set here. Although the group 5 people have some understanding on the relationship among the elements, they are not yet ready to organize their knowledge. The elements are placed somewhere out of the set they are supposed to be in and there is no concept of which element is core and which one is secondary in terms of roles in the set.

Discussion

As learning advances beyond initial learning phase, learners begin to focus less on declarative knowledge and more on procedural knowledge(Anderson, 1982; Kraiger, Ford, & Salas, 1993). Although the network of the model and groups 1 through 5 share the same declarative knowledge of 29 elements, the relatedness among the elements develops less or more depending on the level of knowledge organization that each group has accomplished. As procedural knowledge increases, meaningful structures for organizing knowledge are developed. Since the procedural knowledge are tacit and abstract in nature, it cannot be directly captured. In this study we used the method of representing knowledge structures. These structures are called mental models.

There are two important characteristics in mental models(Ford, Kraiger, & Salas, 1993). One is the type or complexity of the stored elements. The domain-general nodes and domain-specific nodes that the model creates are better organized and more complex than those lower level groups create in our study. The other is the organization or interrelationships among model elements. Experts' knowledge base are more strategic than novices' in the sense that knowledge elements are organized to facilitate knowledge acquisition and application. Each element was more related to other elements within the set which the element is a part in than to other elements outside the set in our study.

We cannot get a complete account of the core skills and knowledge merely by asking experts to list them. We believe that experts are more likely to be able to explicate these skills in the context of different knowledge structure. With a particular difference to talk about, experts can be prompted to descrie what they would do and why. Then we can have a window on the knowledge and skills experts employ with the elements in the list. We called for a focus group interview with the three experts to interpret the difference of the representation observed among groups together.

Our approach of representing and assessing relationship among knowledge elements as revealed in a network representation differs from similar techniques such as multidimensional scaling and hierarchical cluster analysis. Network representation “highlight the local relationships among the entities represented … compared to spatial scaling methods[e.g.: MDS], networks focus on the closely related(short distance, high similarity) entities [to reflect general associative information regarding the state of a cognitive system]. … In contrast, spatial methods are superior in extracting global properties of a set of entities in the form of dimensions of the space … Based as it is on finding minimum paths connecting entities, Pathfinder tends to give greater weight to the smaller distances in the distance estimates(Schvaneveldt, Durso, & Dearholt, 1985, p.26). When MDS and Pathfinder are employed together, we can obtain an underlying dimensional structure with global configuration as well as the most salient pairwise relations among the entities. In this study we had a focus of demonstrating the application of Pathfinder algorithm.

Pathfinder can reveal tree structures in the data as hierarchical cluster analysis does. Often data can be better represented by non-hierarchical and more complex structures that are not constrained by hierarchical restriction. In this case, Pathfinder works excellent. Pathfinder can also suggest “clusters of entities in the form of interconnected subsets of the entities or cycles in the network”(Schvaneveldt, Durso, & Dearholt, 1985, p.26).

Finally we present a suggestion for training professionals. Current training does not provide the kind of practice that enables trainers to cope with the nonroutine problems that are not detected until it is too late to cope with. Formal training emphasizes general facts and principles taught in declarative form on the one hand and traditional rote procedures on the other. In many cases, there is little or no opportunity in the training center to practically upgrade the knowledge and skills of the trainers. Neither is there extensive practice on nonroutine problems during the off-duty hours. In the duty hours, emphasis is placed on keeping the system in operation. The approach we employeed here could trigger the curiosity of trainers so that they are attracted to understanding why one's knowledge representation is different from those of others. Then we could expect a voluntary effort of resolving the difference among the trainers, resulting explication of tacit knowledge into an explicit one and improvement of organizational knowledge.

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