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Application of Structural Representation in Assessing Knowledge Structure of Organizational Members*

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In this study, we report methods and some results concerned with explicating the nature of knowledge of industrial trainers who are at different levels in expertise. Working with the three senior trainers in the training center of a large business group, 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 knowledge elements are concepts, propositions, or practical know-hows of which the trainers should have a good grasp. The rating task was presented to employees with all possible pairs of knowledge 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 representations and worked with a small group of experts to identify the detailed level-specific facts and to understand the differentiation among the groups of trainers.

key words : knowledge structure, network scaling, knowledge representation

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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 individuals knowledge by presenting the individuals 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 relationships among the knowledge elements are not particularly relevant. 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. 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 procedural 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 to assess the configuration in the representation. This configuration could represent procedural knowledge as well as declarative knowledge.

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. This type of approach has already prevailed in the research of semantic memory (e.g., Goldsmith & Johnson, 1990; Schvaneveldt et al., 1985).

Knowledge Assessment and Representation

As learning process advances beyond initial phases, we expect organizational members to focus less on declarative knowledge and more on procedural knowledge which is a beginning of skill and difficult, if not impossible, to retrieve verbally. Then representation should come first and assessment comes later thereupon. To the extent that some relevant knowledge is hard to retrieve verbally, 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 in a specific domain.

Although there are numerous strategies for measuring knowledge structure as in Flanagan (1990), structural assessment is recommended (e.g., Kraiger, Ford, & Salas, 1993) and 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 judgments 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 et al., 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 et. al., 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. The larger the weight is, the longer the distance is. 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 employed in this study is Pathfinder (Schvaneveldt et. al., 1985). Pathfinder produces estimates of all of the pairwise distance between nodes to be mapped on to networks. With the same number of nodes we can draw a lot of different networks. The objective of employing a network scaling method is to define a parsimonious network that includes important links, resulting in 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.

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

This expression can also be applied to defining the length of a path in a network. Let di be the distance associated with link i in a path. The set of all distances in a path with N links is given by di 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. Usual values of r are 1 for a city-block distance model, 2 for a Euclidean distance model, and 8 for a dominant metric model. Pathfinder generates a unique network structure only for $r=\infty$ when the MIN network is generated. When the measurement level is ordinal as is usual in behavioral or social sciences, $r=\infty$ 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 et. al., 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.

With ordinal level data we are particularly interested in a network of ($r=\infty$, $q=n-1$). 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 representations and the progress of domain knowledge. We hypothesized that people or groups of people whose structure more closely matches the role models in the organization will indeed be more knowledgeable and evaluated highly by their supervisors. Relatedness of knowledge structure in the case of undirected graphs with a common set of nodes was measured by the set-theoretic index C which stands for closeness. The index C was developed and validated by Goldsmith and his colleagues (Goldsmith & Davenport, 1990; Goldsmith & John, 1990; Goldsmith et al., 1991).

Suppose there are two groups such as in figure 1.

Here we show in detail how the index C is computed to determine the similarity between

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Graph1 :   C --- A --- B --- D --- E
Graph2 :   B --- A --- E --- C
                       |
                       D
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Figure 1. Two Graphs

the two graphs.

Table 1 shows the steps for computing C. First, the neighborhood set for each node in Graph1 and Graph2 is shown by listing those other nodes that have direct connections to it. Next, the intersection and union of the neighborhood sets between the two graphs are determined for each node and the size of the sets are recorded. The quotient of the size of the intersection set divided by the size of the union set is computed. Finally, C is determined by taking the mean of these quotients across the five nodes. The number of common links given in the intersection column is the most critical element in computing C. In Pathfinder a null hypothesis that C in population is zero is tested. If this probability is very small (e.g., 0.05), we interpret that the two graphs are close or similar. Goldsmith and Johnson showed that their index C was more predictive of performance than other indices not based on configural information.

Goldsmith et al. (1991) evaluated the validity of the Pathfinder scaling algorithm to assess

Table 1. *Method for Calculating C Between Graph1 and Graph2 from Figure 1*

	Neighborhood		Intersection		Union		
Node	Graph1	Graph2	Set	Size	Set	Size	Quotient
A	{C,B}	{B,D,E}	{B}	1	{B,C,D,E}	4	1/4=.25
B	{A,D}	{A}	{A}	1	{A,D}	2	1/2=.50
C	{A}	{E}	U	0	{A,E}	2	0/2=.00
D	{B,E}	{A}	U	0	{A,B,E}	3	0/3=.00
E	{D}	{A,C}	U	0	{A,C,D}	3	0/3=.00

Note. Sum of quotients=.75, C=.75/5 nodes=.15, U=empty set.

students cognitive representation of classroom learning. Judgments data of students and the instructor were submitted to Pathfinder to create knowledge structure. The similarity between each students and the instructors 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 is concurrent with learning. In Kraiger and Salas (1992, recited from Kraiger et al., 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 comprised of 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 senior trainers in the center. We and the senior trainers worked interactively with each other since the climate in our working group was very democratic and flexible. Finally we 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 as shown in the table 2.

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. *The Final Set of Knowledge Elements abbreviated*

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

table 2.

Subjects and Procedure

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

We expect employees in an organization to learn a lot through implicit learning, resulting in implicit knowledge that is difficult, if not impossible, to describe in an explicit manner. That is why we approach their knowledge by collecting proximity judgments that demand minimal retrieval effort. 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, pair comparisons, and 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 in a more differentiated and integrated cognitive system. In this system both declarative knowledge and procedural knowledge would be included. However, the proximity data will provide a good source especially for assessing procedural knowledge which is extremely difficult to assess with direct questions (Goldsmith & Johnson, 1990).

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 varied 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 senior trainers were combined and averaged. We call this data the role models data or just the models data. We analyzed 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($r=\infty$, $q=n-1$) 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 and the indirect measure of relatedness for each pair of items. Suppose there are items i and j. The indirect measure of proximity between i and j is obtained by correlating the proximities between the item i and all other items except j, and the proximities between the item j and all other items except i. The coherence measure reflects the consistency of the data. Very low coherence values(less than .20 or so) indicate that ratings were not performed seriously (Schvaneveldt et al., 1985). The coherence of the models 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, thus leading us to exclude their data from further analysis. We will present the results from comparing the models data with the remaining 18 trainers from now on. Pathfinder representations 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.

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 job performance. Our hypothesis that employees of high similarity with the model will be highly evaluated is supported. In the study of Goldsmith and Johnson (1990), this correlation was .74 from 40 participants which was very high. In the study of Goldsmith and Johnson, the criterion variable was learning, in contrast to job performance in the present study. Since the index C represents the level of knowledge, it is not surprising that C is correlated with learning higher than with job performance. Moreover, we had only 18 participants included in the evaluation, which could result in the restriction of range. Agreement of knowledge representation

Table 3. *Analysis of 18 Trainers 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 each participant on a 9 points scale. Inter-rater reliability was .83.

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 improve the parsimony of explanation and the reliability of measurement. Based on the values of C index in the table 3, we categorized 18 participants into 5 groups as in table 4.

The groups in table 4 are in the order of C values. But they are not necessarily in the order of performance as we see from the imperfect correlation between the C and performance data. The coherence values of each group data are higher than those of individuals data in each group except H. This represents that grouping was done for similar individuals.

In figure 2 we present the network of the model, and those of groups 1 through 5. We have hypothesized earlier that groups with high values of C will be more knowledgeable. This hypothesis will be tested by examining the difference between the network of the model and that of each group. Here we are not going to provide a formal statistical testing, but a qualitative interpretation of knowledge structure which could be labeled as schema. The concept of schema is the most commonly used construct to account for complex knowledge structure. A schema is defined as a structured cluster of concepts; usually it involves generic knowledge and may be used to represent events, sequences of events, percepts, situations, relations, and even objects (Eysenck & Keane, 2000, p.252). The knowledge elements in table 2 include some of generic knowledge such as understanding the

Table 4. *Grouping of the Participants*

Group	Participants	Coherence	Common links*	C	p-value**	mean of performance
1	G, I, N, O	.72	17	.25	.00	6.21
2	B, C, Q, R	.58	17	.22	.00	5.06
3	D, E, F, K	.65	13	.17	.00	5.44
4	H, J, P	.79	11	.14	.00	6.05
5	A, L, M	.56	9	.10	.09	5.48

* 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.

Group, vision of the training center, roadmap of the center, history of the center and etc. The knowledge elements in table 2 also include events or sequences of events such as flow of training operation, use of instructional equipment and material, use of office automation system and machines, and etc. Some elements are very complicated cluster of concepts involving generic knowledge, sequence of events, percepts, situations, relations, and objects. Examples are such elements as understanding the culture of the training center, understanding the structure and operation of the training center, and etc.

Based on the meaning of the nodes in the network, we can interpret how knowledge structure changes as the C values get higher. Since our hypothesis is that groups with high values of C will be more knowledgeable, we will demonstrate how the knowledge structure gets more refined as we go over from group 5(lowest C value) through group 1(highest C value) in comparison with the model in figure 2.

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 senior trainers 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 3.

The right half of the network in the model is about domain-general knowledge such as road map, vision of the center, structure and operation of the center, and knowledge about

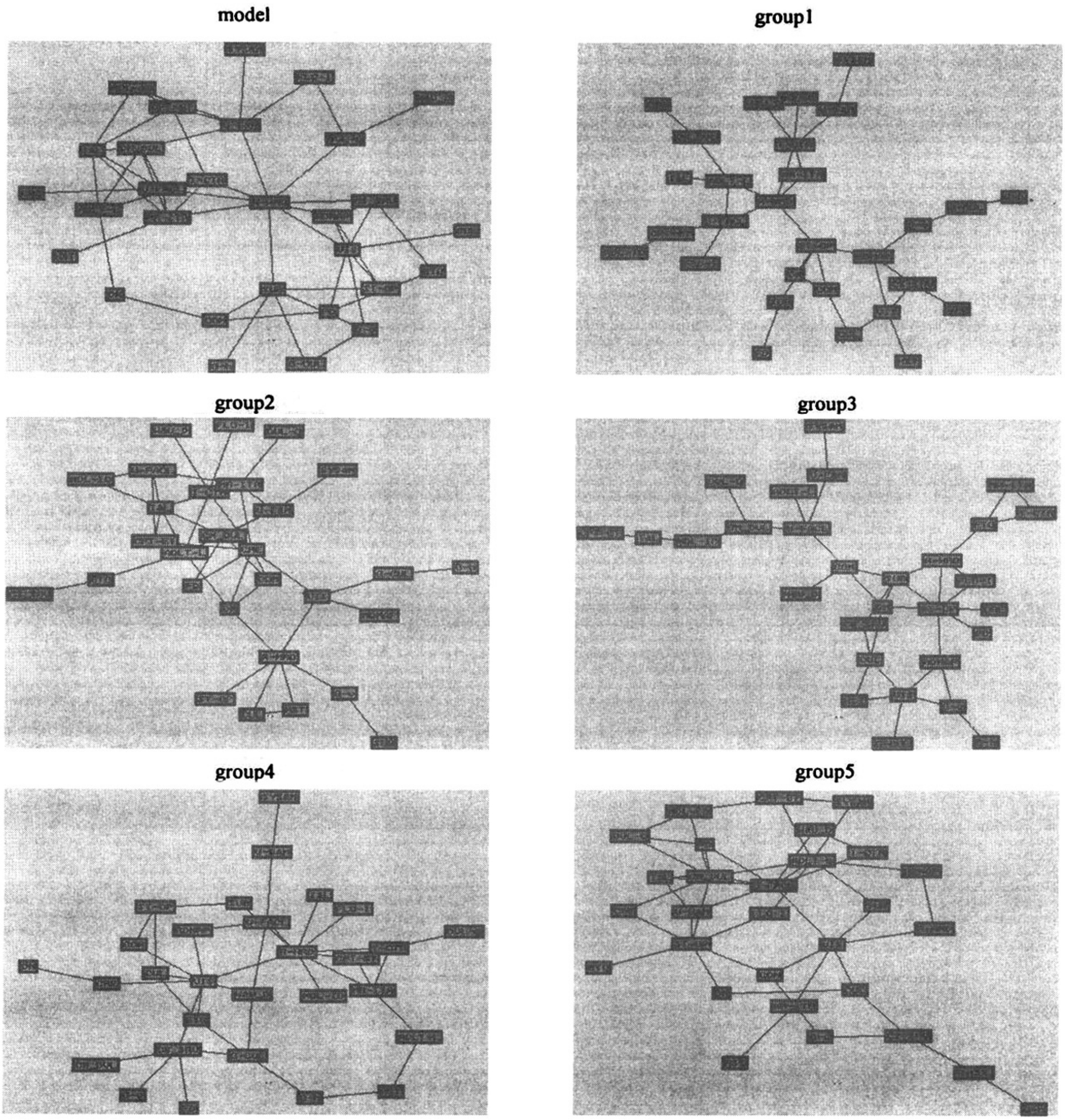

Figure 2. Network Representation of the Model, groups 1 through 5.

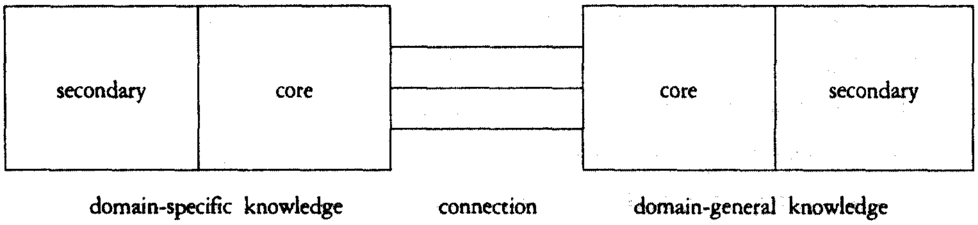

Figure 3. Schema of Interpretation

subsidiaries that serve as environment in operating the training center. The right-half represents an environment-related knowledge set. The left-half of the network is about domain-specific knowledge that is 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. The left-half represents a production-related knowledge set.

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 effort when they are needed. The connection between the two halves in the network represent the degree to which the participants have a good grasp of associating domain-specific knowledge with domain-general knowledge. In figure 2, the models network shows clear delineations of environment-related knowledge set and production-related knowledge set, and core knowledge and secondary knowledge. Also it shows a connection of appropriate degree between left-half and right-half in the figure. The degree of connectedness is neither too much nor too scant.

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. We hypothesized that the deviance would get more serious as we go over from group 1 through group 5.

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 models network are connected to the training-related knowledge set (e.g.: CS_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 in 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 found in the domain-general set(e.g.: R-HRD, FL0-I, CRE, ETQ, MR-ITR, T-CTR). 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, group 3 people have more emphasis on the domain-general. 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 setting aside that 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, but, 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 they seem to have no concept of which element is core and which one is secondary in terms of roles in the set.

Discussion

Although the network of the model and groups 1 through 5 share the same knowledge elements, the relatedness among the elements develops less or more depending on the level of knowledge organization that each group has accomplished. As the knowledge gets more organized, meaningful structures emerge. As learning advances beyond the initial learning phase, learners begin to focus less on declarative knowledge and more on procedural knowledge (Anderson, 1982; Kraiger, et. al., 1993). Since the procedural knowledge is tacit and abstract in nature, it cannot be directly captured. In this study we used the method of representing knowledge structures.

The domain-general set and domain-specific set that the model creates are better organized and more complex than the groups created in our study. The senior trainers knowledge base is 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 the present study.

We cannot get a complete account of the core skills and knowledge merely by asking experts to list them. We believe that experts like the senior trainers in our study 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 describe what they would do and why. Then we can get access to the knowledge and skills experts employ with the elements in the list. We called for a focus group interview with the three senior trainers to interpret the difference of the representations 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 is focusing on the local relationships among the entities represented. Compared to spatial scaling methods (e.g., MDS), network scaling highlights the closely related(high similarity) entities to reflect general associative information in ones 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 et al., 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 focused on 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 et al., 1985, p.26).

Current practice of training in organizations 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 sessions emphasize on 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 employed here could trigger the curiosity of trainers so that they are attracted to understanding why ones knowledge representation is different from those of others. Then we could expect a voluntary effort of resolving the difference among the trainers, resulting in explication of knowledge structure into a more formal and refined one.

The knowledge structure the trainers have could be labeled a schema. However, the interpretations we provide here are only in an ad hoc fashion. Although the theory of schemata explains much the structure and organization of knowledge, there is a broad consensus that schema theories are unprincipled (Eysenck & Keane, 2000, p.256). Our schema-theoretic interpretations are not predictive, but in an ad hoc fashion. We need a follow-up study to upgrade this schema-theoretic explanation to mental models that are predictive.

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조직구성원의 지식구조 분석을 위한 구조적 표상의 응용

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이 연구에서 우리는 전문성에 있어 상이한 수준에 있는 산업훈련 담당자들의 지식을 연구하는 데 관련된 방법 및 결과를 제시하고 있다. 어느 대기업 연수원의 선임훈련자 3명과 작업하여 그 연수원내 전문 훈련자로서의 역량으로서 필요한 29개의 핵심요소를 정의하였다. 이 지식 요소들은 훈련자들이 잘 알아야 하는 개념이나 실제적 노하우들이었다. 연수원내 응답자들에게 이들 핵심요소들이 짝지어 제시되었고, 각 짝내의 요소들간에 관련성을 10점 척도를 사용해서 평정하도록 요구하였다. 21명의 응답자들이 평정을 완료하였다. 두 요소간 관련성의 평정 수치가 낮을수록 개인의 지식구조에서 그 두 요소간 거리는 멀 것으로 가정된다. 평정결과는 Pathfinder라고 하는 지식구조 표상의 알고리즘에 입력되어, 요소는 매듭으로 관계는 매듭간 연결선으로 나타나는 연결망이 산출된다. 그 결과로 훈련자들의 역량수준별 지식구조가 달리 표상되었고, 훈련자 집단간의 차별화에 대한 이해를 더하게 되었다.

주요어 : 지식구조, 네트워크 스케일링, 지식표상