Emerging organizational structure for knowledge-oriented teamwork using genetic algorithm

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ARTICLE INFO

Keywords: 
Match 
Organizational structure 
Knowledge sharing and support 
Genetic algorithm

ABSTRACT

Organizations have historically sought efficiency improvements through different combinations of materials, components, production and processes to get better performance. However, in this age of the knowledge economy, the new organizational management has shifted its focus to the proper use of the knowledge of employees to create greater output and performance. There is a recent trend towards flat organizations and team-orientated structures, therefore this study will concentrate on the knowledge-oriented teamwork. To construct the fitting team structure, we solve the problem in two stages. In the first stage, we assign the proper tasks to the proper members to achieve a good match for effective usage of organizational knowledge. In the second stage, we solve the problem of insufficient knowledge within the organizational structure generated in the first stage by adjusting the positions of members to improve the mutual coordination and knowledge sharing and support.

We applied a basic genetic algorithm (BGA) to solve the problems in both the stages. Five factors, such as member/task number, the number of knowledge types, the number of task types, the average complexity of each member’s knowledge types and the average complexity of task knowledge types, are considered to generate different types of problems. Computational results show that the BGA is able to find optimal knowledge matching for small-sized problems in the first stage, and that the BGA is able to improve the organizational structure generated in the first stage in order to reduce the communication cost of knowledge support among the members in the second stage.

1. Introduction

Drucker (1999) said, “The most valuable assets of a 20th-century company were its production equipment. The most valuable asset of a 21st-century institution, whether business or non-business, will be its knowledge workers and their productivity.” Today, managers are increasingly regarding knowledge as an important resource; together with the monitoring of capital flow, component flow and material flow, the management of knowledge flow within the organization has also become an essential part of managers’ responsibilities (Amidon, 2001; Walczak, 2005). In order to use knowledge assets effectively, organizations should make proper decisions and coordination to prompt improved combinations of knowledge (Buckley & Carter, 2004). Much research has focused on issues concerning knowledge applications such as how information systems can be used to support the creation, transfer and application of knowledge within an organization (Alavi & Leidner, 2001); and in providing methods to measure and assess the contribution of knowledge to business value (Ahn & Chang, 2004; Chen & Edgington, 2005). The common purpose of these studies is to enable organizations to maximize the benefits of the knowledge available within them.

Two important factors considered by managers in tackling problems involving the effectiveness of organizational knowledge utilization are the tasks at hand and the members of the team available to execute the tasks; optimal combinations of the two typically result in good organizational performance. However, it should be noted that the managers need to provide a pleasant and supportive organizational structure to facilitate their team members’ productive execution of the assigned tasks. In Cowan and Jonard (2004), Tata and Prasad (2004), the authors used calculation models to simulate the influences of the adjustments to the organizational structure on the knowledge and innovations in an organization. The results showed that the structure of a knowledge-oriented organization indeed affects the creation and diffusion of knowledge.

The formation of teams and groups within organizations has become a popular trend and this has corresponding effects on organizational structure. This was mainly driven by the momentum and speed of response afforded by a team environment. In fact, many companies now use project teams to deal with the changing environment (Kerzner, 2001). Bishop (1999) stressed the dynamic capability and timeliness of task-oriented teams. To build a new
century business organization, managers must form project teams with competent people and strengthen their information sharing capabilities. Since the 90s, the information sharing and knowledge management in the project-based organization (Cicmil & Hodgson, 2006) have been investigated in the literatures. Recently, an increasing number of researchers have discussed issues about knowledge sharing and organizational structures including Walczak (2005), who proposed and evaluated a management structure that encourages knowledge sharing across an organization. Riege (2005) recommended that managers should notice some knowledge sharing barriers including the problems of organizational structures.

The formation of project teams and the application autonomous management is now widely adopted in the practical environment by companies such as General Motors Corporation, P&G Global Corporation, Federal Express Corporation and Westinghouse Electric Corporation (DeCanio, Debble, & Keyvan, 2000). Furthermore, the research in Gordon (1992) showed that 82% of US companies with 100 or more employees used teams. In 1987, self-managing work teams and employee participation groups were adopted by 28% and 70% of Fortune 1000 firms, respectively, these figures have increased to 68% and 91% by 1993 (Lawler, Mohrman, & Ledford, 1995). It is apparent that an increasing number of organizations have come to recognize the value created by team work. Therefore, we focused on the matching of members’ knowledge to the tasks for project teams and further, the support and coordination problems.

The rest of this paper is organized as follows: Section 2, introduces a conceptual model to build the problem of emerging organizational structure for knowledge-oriented teamwork. Section 3 describes the problem in detail and shows a two-stage procedure for solving the problem. In the first stage, we solve the matching problem of knowledge between members and tasks. In the second stage, we achieve the mutual effective support for insufficient knowledge. Section 4 presents the two-stage GA procedure to solve the problem. Section 5 presents a comparison of the performance under different settings such as the number of members/tasks and number of knowledge types. Finally, we put forth our conclusions in Section 6.

2. Conceptual model

In this study, we adopted the Diamond Model of Leavitt (1964) to describe the problems we will solve (see Fig. 1). The model has four components including organizational task, structure, technology and actors. It expresses that the entire performance of the organization is an integrated result of the activities of tasks, structure of organization, technologies and the members involved in the execution. All of them are interdependent in that when one of the components changes, it will lead to a series of adjustments within the whole model.

The Diamond Model developed in this research focuses on the relationship between the member and the task, and on the relationship between the member and the structure. These two relationships are defined as “matching” and “support” (see Fig. 1).

For the purpose of this study, we set forth the following definition of terms:

**Task:** Tasks are all kinds of works and assignments in an organization. This study uses the different types of knowledge that tasks require to represent the characteristics of tasks.

**Member:** Members are the people who execute the works and assignments. They usually possess the conceptual background, skills and knowledge required for the execution of their tasks. They also have the motivation and responsibility to complete tasks. Sometimes, communication and cooperation are necessary for the execution of their jobs. We use the different types of knowledge that members possess to represent the characteristics of members.

**Structure:** The composite of functions, relationships, responsibilities, authorities, and communications of the members within an organization.

**Matching and support:** “matching” results in a “right member – right task” combination and refers to the assignment of the appropriate person to the appropriate task. “Support” results in a “right member – right position” combination and refers to the deployment of the appropriate person to the appropriate position within the organizational structure. This will enhance the function of mutual communication and cooperation.
According to the model we have developed, we examined the matching of the members to the tasks and then produced the organizational structure that supports effective communication and knowledge sharing among the members.

3. Problem statement

The problem pertains to the development of an optimal organizational structure for knowledge-oriented teamwork. Fig. 2 illustrates an example in which an organization has an organizational leader (L), two projects (Pi) to accomplish and some members (mi) available for the execution of the tasks. The projects comprise several teams (Ti), units (Ui) and tasks (ti). To construct the suitable structure for organizations to effectively use their knowledge, we have considered not only the matching between mi and ti, but also the knowledge sharing and support among mi in the decision to allocate members to a specific Pi, Ti and Ui. Therefore, the problem is solved in two stages: first, determine the knowledge matching between members and tasks and then, determine the positions of the members to facilitate knowledge sharing and support.

3.1. Knowledge matching between tasks and members

In the matching problem, each member possesses some types of knowledge and each task requires some forms of knowledge for its completion. Hence, the problem is to assign the specific members to specific tasks with the goal of maximizing the knowledge matching (or minimizing the knowledge mismatch) while considering the one-person-one-task constraint. The following notations are used to describe a knowledge matching problem in this research.

Given that N is ten, Kn is six and Tn is three for an organization and that each member m1 \ldots m10 is assigned to only one of the tasks. All types of organizational knowledge are represented by \( k_1, k_2, k_3 \). The number of tasks in the three task types \( t_1, t_2, t_3 \) is 4, 3, and 3, respectively. The number of knowledge types that each member possesses and that each task type requires is assumed to have normal distributions with positive parameters \( \mu_{m_{n_{k}}}, 1 \) and \( \mu_{t_{n_{k}}}, 1 \). We set \( \mu_{m_{n_{k}}} \) as the product of \( Kn \) and \( p_{m_{n_{k}}} \) and \( \mu_{t_{n_{k}}} \) as the product of \( Kn \) and \( p_{m_{n_{k}}} \). Here \( p_{m_{n_{k}}} \) and \( p_{m_{n_{k}}} \) are 40%, so both \( \mu_{m_{n_{k}}} \) and \( \mu_{t_{n_{k}}} \) are 2.4. The generated numbers are rounded and used to generate the knowledge types based on uniform distribution. Take \( m_1 \) as an example. Using the normal distribution N (2.4, 1), we have determined that the number of knowledge types \( m_{1} \) possesses is 3. Then, the uniform distribution produces three numbers 1, 2, and 5 as the index of knowledge types for \( m_1 \). The problem in the first stage of this research has been developed according to the above parameter settings. The characteristics of each member and task are listed in Table 1. The key point of the problem in the first stage is to bring forth the optimal knowledge matching results through the proper assignment the member \( m_1 \ldots m_{10} \) to the task type \( t_1 \ldots t_3 \).

3.2. Knowledge sharing and support among members

To survive and thrive in a continuously changing environment, flat organizations and the use of project teams have become prevalent forms of organizational structure. Communication and information/knowledge sharing and support among the members are particularly emphasized here. Therefore, managers should create an environment that inspires members to naturally support each other. For this purpose, we construct the teamwork structure under the established hierarchical relationship. Every member will stay at his suitable position in this structure, with the aim of reducing obstructions when the members call for support from others.

Mutual coordination and knowledge sharing means that when a member’s knowledge is not sufficient to meet all the requirements of his task, another person who has the knowledge can give some suggestions and provide support to him. Nevertheless, there is a cost involved in communication and coordination when someone calls for support; further, calls for support to other units or teams may entail even more cost. We will solve this problem and lower the cost of communication by finding out the effective knowledge combination of the organization with a structure view.

The first stage generated the result (see Fig. 3) that the managers should assign task type \( t_1 \) to members \( m_1, m_2, m_5 \), and \( m_6 \); \( t_2 \) to \( m_3, m_4, m_5 \), and \( t_3 \) to \( m_4, m_9, m_10 \). We then determined the positions of all members \( m_1 \ldots m_{10} \) within the organizational structure in the second stage. The problem in the second stage is to determine which of the \( t_1 \) tasks should be assigned to \( m_1, m_2, m_5, m_6 \), respectively; which of the \( t_2 \) tasks should be assigned to \( m_3, m_4, m_5 \), respectively; and which of the \( t_3 \) tasks should be assigned to \( m_4, m_9, m_10 \), respectively. The communication cost between members is defined as the management cost entailed by time, human resources and devices for coordination and communication. In this research the communication cost, \( C_{ij} \), between members \( i \) and \( j \), is defined to be the length of the path required for their communication.

Table 1

<table>
<thead>
<tr>
<th>Knowledge Types the members possess</th>
<th>Knowledge types the tasks require</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_1: (k_1, k_2, k_3) )</td>
<td>( t_1: (k_2, k_3, k_4) \times 4 )</td>
</tr>
<tr>
<td>( m_2: (k_1, k_4, k_5) )</td>
<td>( t_2: (k_1, k_3) \times 3 )</td>
</tr>
<tr>
<td>( m_3: (k_1, k_4, k_5) )</td>
<td>( t_3: (k_2, k_3, k_6) \times 3 )</td>
</tr>
<tr>
<td>( m_4: (k_4) )</td>
<td></td>
</tr>
<tr>
<td>( m_5: (k_5) )</td>
<td></td>
</tr>
<tr>
<td>( m_6: (k_5) )</td>
<td></td>
</tr>
<tr>
<td>( m_7: (k_6, k_7) )</td>
<td></td>
</tr>
<tr>
<td>( m_8: (k_6, k_7) )</td>
<td></td>
</tr>
<tr>
<td>( m_9: (k_6, k_7) )</td>
<td></td>
</tr>
<tr>
<td>( m_{10}: (k_8, k_9) )</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2. The knowledge matching and support problem.
For example, in Fig. 3, the communication path between \( m_1 \) and \( m_2 \) is \( m_1 \rightarrow U1 \rightarrow T1 \rightarrow U2 \rightarrow m_2 \), so the length of the path of four is the communication cost between \( m_1 \) and \( m_2 \). Note that the communication needed between \( m_1 \) and \( m_2 \) occurs because \( m_1 \) lacks the knowledge \( k_4 \) to execute his task \( t_1 \) and \( m_2 \) possesses aforesaid knowledge. The objective in the second stage is to minimize the total communication cost among the members.

4. Applying genetic algorithms (GAs) to solve the candidate problem

GA is a search method that mimics the biological process of natural evolution and the idea of the survival of the fittest. Starting with a population of randomly created solutions, the solutions with better fitness are more likely to be chosen as a parent to produce new solutions (offspring) for the next population (generation). The objective value of a solution is the measure of its fitness. The fitness of the solutions would be improved in the next generation as the iteration progresses.

The procedure of GA, which is mainly drawn from the study of Chen, Neppalli, and Aljaber (1996), Chen, Vempati, and Aljaber (1995) can be described as follows. Let \( S(t) \) denote the population in the \( t \)-th generation, \( s_i(t) \) denote the \( i \)-th member in \( S(t) \), \( f_i \) denote the fitness of \( s_i(t) \), \( Totfit \) denote the sum of \( f_i \) in \( S(t) \), \( popsize \) denote the population size, and \( maxgen \) denote the maximum number of generations for convergence. Then a basic GA usually has the following steps.

Step 1: Generate an initial population, \( S(t) \), where \( t = 0 \).
Step 2: Calculate the fitness value for each member, \( f_i \), in population \( S(t) \).
Step 3: Calculate the selection probability for each member, which is defined as \( f_i/Totfit \).
Step 4: Select a pair of members (parents) randomly according to the selection probability.
Step 5: Apply genetic operators to the parents to produce the offspring for the next generation, \( S(t+1) \). If the size of the new population is equal to \( popsize \), then go to Step 6; otherwise, go to Step 4.
Step 6: If the current generation, \( t+1 \), is equal to \( maxgen \), then stop; otherwise, go to Step 2.

According to the basic procedure, the application of a GA must consider the following factors: (1) initial population, (2) selection probability, (3) genetic operators, (4) termination criterion, and (5) three parameters: population size, crossover rate, and mutation rate. In the following, each of these factors and parameters will be discussed for a GA to generate the optimal team structure for the effective usage of knowledge within an organization.

4.1. Application of GA to the knowledge matching problem in the first stage

1. Initial population.
A solution for GA applications is usually represented by a row vector. In this study, the elements in a vector refer to the serial number of the members and it is according to the order and quantities of task types. The GA solution for the member-task matching in Fig. 3 is presented in Fig. 4: the first four elements correspond to task type \( t_1 \), the next three elements correspond to task type \( t_2 \), and the last three elements correspond to task type \( t_3 \). The number of elements \( N \) in a vector depends upon the number of members in the organization.

2. Selection probability.
The selection probability of a solution in a population should generally project the performance measure of the solution. Usually, a solution with a better fitness in a population would have a higher probability of being selected. The fitness value of a solution is the number of unmatched knowledge between organizational members and tasks. For instance, according to the data presented in Table 1, the knowledge types that member \( m_1 \) possesses are \( k_1 \), \( k_2 \) and \( k_5 \), and the knowledge types that task type \( t_1 \) requires are \( k_3 \), \( k_4 \) and \( k_5 \), so the matched knowledge between \( m_1 \) and \( t_1 \) is \( k_1 \) and \( k_3 \), and the unmatched knowledge is \( k_2 \) that member \( m_1 \) lacks to finish task type \( t_1 \). In order to solve the minimization problem, we use the following procedure of the well-known roulette-wheel selection scheme for calculating the selection probability of a member in a population.

Step 1: Calculate \( f_i = f_{max} - f_i \) for each member in the population, where \( f_{max} \) is the greatest value in all \( f_i \).
Step 2: Calculate the total fitness, \( Totfit \), of all the members in the population.
Step 3: Calculate the selection probability for each member that is equal to \( f_i/Totfit \).
3. Genetic operators

Genetic operators are performed on the parents to generate an offspring. Crossover and mutation are two common genetic operators of GA. In this research, we adopt the partially mapped crossover (PMX) operator that is developed by Goldberg and Lingle (1985). The main steps are depicted below:

Step 1: List the two chromosomes of parents P1 and P2 in a parallel manner. The number of members is ten in this example.

\[
P1 = 6 \ 2 \ 4 \ 7 \ 10 \ 1 \ 8 \ 3 \ 9 \ 5 \\
P2 = 7 \ 5 \ 9 \ 2 \ 8 \ 10 \ 4 \ 3 \ 6 \ 1 \\
\]

Step 2: Select two corresponding blocks in P1 and P2 randomly and exchange the elements in the blocks. We select the fourth element to the seventh element as the block in this example. After the exchange of the elements in the chosen blocks, the two chromosomes shown above become the new ones shown below.

\[
P1 = 6 \ 2 \ 4 \ 2 \ 8 \ 10 \ 4 \ 3 \ 9 \ 5 \\
P2 = 7 \ 5 \ 9 \ 7 \ 10 \ 1 \ 8 \ 3 \ 6 \ 1 \\
\]

Step 3: Adjust the repeated figures in the non-gray blocks of P1 and P2. After the above steps, both the chromosomes P1 and P2 have repeating figures and need to be adjusted and modified. In the gray blocks, the elements of P1 and the elements of P2 are paired off such that each of the (2 and 7), (8 and 10), (10 and 1) and (4 and 8) are in pairs. We adjust the repeated figures in the non-gray blocks of P1 and P2 according to the gray blocks. For example, in P1, the numeral 2 is repeated, so we replace the second element with 7 based on the implication in the gray block that (2 and 7) are a pair. The numeral 4 is also repeated, and therefore the third element is replaced with 8 because {4 and 8} are a pair in the gray block. However, the new figure 8 is still repeated and has to be replaced following the same paired information, so it is replaced with 10. The numeral 10 is still repeated and therefore it is replaced with 1. This process has eliminated repetitions in chromosome P1. The same process is used to adjust the other chromosome, P2. Finally, two chromosomes complete the crossover and create the offspring as follows.

\[
O1 = 6 \ 7 \ 1 \ 2 \ 8 \ 10 \ 4 \ 3 \ 9 \ 5 \\
O2 = 2 \ 5 \ 9 \ 7 \ 10 \ 1 \ 8 \ 3 \ 6 \ 4 \\
\]

The mutation operator, on the other hand, involves the selection of two elements randomly in a chromosome and swaps the elements. It always applies to a single chromosome; for example, we randomly choose the two elements three and six of the chromosome given below.

\[
M = 7 \ 3 \ 8 \ 9 \ 2 \ 5 \ 10 \ 1 \ 6 \ 4 \\
\]

We can easily get the new mutated chromosome by swapping the two elements as follows.

\[
M = 7 \ 3 \ 5 \ 9 \ 2 \ 8 \ 10 \ 1 \ 6 \ 4 \\
\]


All these parameter values are determined by trial-and-error method in this research; the population size is 100, crossover rate is 0.85, mutation rate is 0.15 and the termination criterion is 50 generations with no improvement in the objective value.

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4.2 Application of GA to the knowledge support problem in the second stage

The solution generated in the first stage is used to generate the initial population in the second stage. We assume the solution generated in the first stage to be the one shown in Fig. 5. The solution has three segments that present the corresponding task types. Each element of the solution is not assigned the task type but the certain task \( t_i \). For example, the first element \( m_1 \) is assigned to task \( t_{11} \), the second element \( m_2 \) is assigned to task \( t_{12} \), and so on. The application of GA in the second stage is to optimally determine which member should be assigned to which \( t_i \) in the same segment (task type) so that the total communication cost can be minimized; that is to say we want to determine the optimal sequence of the members in each segment. Given the following solution, by applying the same GA to the problem in the second stage, a solution in the initial population can be generated by combining a random sequence of the members in the first segment, the second segment, and the last segment. The genetic operators are then applied to the segments of solutions separately. For instance, given a pair of parents, the PMX crossover operator is applied to each of the three segments separately to produce two offspring.

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5. Experiments and performance assessment

In this section, we assess the performance of the basic GA (BGA) used in this research. In the first-stage problem, since no effective methods exist for finding the optimal solution, we compare the results of BGA to the results of the exhaustive search method (ESM). ESM is a basic method for finding out all possible solutions; therefore, results are generated with absolute accuracy. However, this will usually entail too much computation time, so only small-sized problems are generated for comparison. In the second-stage problem, as discussed previously, we use the solution generated in the first-stage problem as the input for the second-stage problem. To evaluate the improved performance by BGA, we compare the communication cost of the solution generated in the second stage with that generated in the first stage.

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Table 2: The number of optimal solutions that the BGA can find.

<table>
<thead>
<tr>
<th>Exp. No.</th>
<th>( N )</th>
<th>( K_n )</th>
<th>Execution precision of GA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–10</td>
<td>7</td>
<td>8</td>
<td>100</td>
</tr>
<tr>
<td>11–20</td>
<td>8</td>
<td>8</td>
<td>100</td>
</tr>
<tr>
<td>21–30</td>
<td>9</td>
<td>8</td>
<td>100</td>
</tr>
<tr>
<td>31–40</td>
<td>10</td>
<td>8</td>
<td>80</td>
</tr>
</tbody>
</table>

Table 3: The experimental combinations for the second-stage problem.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>40</td>
<td>60</td>
<td>100</td>
</tr>
<tr>
<td>( K_n )</td>
<td>10</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>( \nu_n )</td>
<td>5</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>( \rho_m )</td>
<td>30</td>
<td>50</td>
<td>80</td>
</tr>
<tr>
<td>( \rho_k )</td>
<td>30</td>
<td>50</td>
<td>80</td>
</tr>
</tbody>
</table>
5.1. Experiments in the first-stage problem

We set the number of decision variables, \( N \), from seven to ten; the number of knowledge types \( K_n \) is set at eight and every task and member require and possess three to six knowledge types. We execute each method ten times for each problem. Table 2 presents the number of times that BGA is able to find the optimal solutions. The results show that BGA is able to find all the optimal solutions except the last problem. In the two experiments of the last problem that BGA is not able to find the optimal solutions, the difference between the solutions generated by BGA and the optimal solutions is one (in one of the experiments, optimal solution = 10 and BGA solution = 11 and in the other, optimal solution = 13 and BGA solution = 14).

5.2. Experiments in the second-stage problem

Five parameters are considered to generate test problems in this stage. The five parameters are the member/task number \( (N) \), the number of knowledge types \( (K_n) \), the number of task types \( (T_n) \), the average complexity of each member’s knowledge types \( (P_{nk}) \) and the average complexity of task knowledge types \( (P_{tk}) \). Three levels are considered for each parameter, resulting in \( 3^5 = 243 \) combinations. Table 3 presents the experimental combinations. One test problem is generated for each combination, so 243 test problems are generated.

For each test problem, the BGA is executed to find the best knowledge matching in the first stage, and the same BGA is executed to improve the organization structure in the second stage. Table 4 presents computational results of the second stage. The results show that the BGA is able to find effective organization structure for knowledge support that decreases the communication cost of the organization structure generated in the first stage by 7.86% on average. This improvement is more significant (about 10%) for the problems with sixty or less number of members/tasks \( (N) \).

6. Conclusions

We have developed a problem based on the Diamond Model of Leavitt to produce the suitable team structure for the effective usage of organizational knowledge. The purpose of the problem in the first stage is to maximize the matching between the members and task knowledge requirements. The purpose of the problem in the second stage is to minimize the communication cost of knowledge support among the members. Therefore, the optimized structure indeed creates more effective usage of knowledge.

The issues of relationships among the members, tasks, and organizational structure are interesting but complex. Although the BGA is able to generate promising organization structure for effective usage of knowledge several factors can be added into the current model for further study such as the project schedules, the time that a member is allowed to support other members, and the training cost for the knowledge that the organization does not have. We believe that in the age of the knowledge economy, quantitative analysis of the performance of knowledge application is important in management issues and is worthy of further study.

References