A Virtual Knowledge Service Team Formation Approach for Dynamic Knowledge-Based Industry Environments

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ABSTRACT: Knowledge commerce (k-commerce) based on electronic commerce has brought innovative concepts and new profit models to enterprises. Profits can be generated for enterprises through repackaging of knowledge and providing customized knowledge-based services. However, diverse and complex enterprise problems exist in the process of knowledge-based industry service that cannot be solved by a single knowledge worker or expert. A high-quality knowledge-based service could be provided by combining professionals with different knowledge backgrounds and expertise into a virtual knowledge service team. Thus, this study proposes a method for forming a knowledge service team based on the capabilities and the cooperative relationship among members. This study also accounts for the relevance of each professional role. The methods mainly include: (1) the role selection method, which involves establishing professional roles required by knowledge service teams according to the knowledge service requirement statement; (2) the member election method for knowledge service teams, which entails selecting competent knowledge workers for each professional role; and (3) the team combination method, which involves organizing an effective knowledge service team. This study effectively established a virtual knowledge service team that integrates individual abilities and team cohesiveness.

Keywords: Knowledge Service Market, Knowledge Worker, Virtual Team, Team Formation, Genetic Algorithm.

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1. INTRODUCTION

In the era of innovation economy, knowledge has become an essential asset for enterprises as well as for the motivation to innovate. Knowledge commerce (k-commerce) involves applying knowledge assets in internal organizations to market the knowledge products or services externally (Skyrme, 2001). The methods for marketing knowledge include transforming knowledge into knowledge products for marketing and using knowledge directly to provide customized services. Implicit knowledge is individually possessed and is not easily revealed. People are carriers of implicit knowledge; therefore, implicit knowledge possessed by people can be used to provide knowledge services. However, this provision often requires linking professionals of various domains from different organizations or regions to form a virtual knowledge service team to fulfill quickly the service requirements of knowledge requesters while facing cross-domain, diverse, and complex enterprise questions. Thus, the approach to efficiently linking professionals from different domains to form a project-based virtual team based on customer needs and providing the knowledge and skills that customers need is a critical development direction involved in knowledge services (Skyrme, 2001; Zhuge & Guo, 2007).

Team members assemble quickly to set common goals and disperse after the goals have been achieved. Excess time spent on integration among members is not allowed. Each team member must fuse to the team as quickly as possible to solve problems efficiently and effectively (Zhuge & Guo, 2007). Therefore, effective team performance depends on the selection of outstanding team members and whether the members can maintain excellent cooperative relationships.

In relevant studies on member selection, the professional abilities of members have been viewed as critical factors for consideration. However, most related literature has discussed only whether members possess professional abilities (Fitzpatrick & Askin, 2005; Tseng, Huang, Chu, & Gung, 2004) or have simply calculated their degree of knowledge according to the number of years they have worked (Chen & Lin, 2004). In addition, Pinjani and Palvia (2013) indicated that deep level diversity has a more significant relationship with mutual trust and knowledge sharing than visible functional level diversity does. Wi, Oh, and Jung (2011) presented a model for quantitatively evaluating the knowledge and collaboration in a semantic web environment of internal and external experts. Guchait and Hamilton (2013) investigated the temporal priority of shared mental models on team learning behaviors. Nevertheless, longevity is not the only factor involved in accumulating professional abilities. Thus, the number of years worked is not an objective representation of the degree of professional ability. Moreover, the work or related experience of members can indicate their professional abilities. Therefore, a more accurate method for evaluating the professional ability of members should be adopted for selecting the most appropriate members.

When discussing team cooperation, most related literature has begun with the cohesiveness of members who establish a team with excellent cooperative relationships (Agustin-Blas et al., 2011; Chen & Lin, 2004; Fan, Feng, Jiang, & Fu, 2009). However, related literature has neglected the notion that the strength of cooperative relationships among members could be affected by various task connections. For instance, members who perform similar roles to solve particular problems may interact more frequently than those who perform different roles. Thus, cooperative relationships among members with similar roles are stronger than relationships among those with different roles. In other words, the cohesiveness among similar roles is considered more influential than the cohesiveness among different roles. Thus, in addition to the cohesiveness among members, the strength of cooperative relationships between similar roles should be considered when establishing a team. In this manner, team members could interact harmoniously. Therefore, it is contributed to the team establishment if role connections for building cooperation relationships among team members are established.

Currently, four difficulties have not been solved for establishing a knowledge service team: (1) the numerous complex evaluation indicators of knowledge service members are difficult to define; (2) the characteristics of workers should be considered in addition to the evaluation and selection indicators of a common virtual team member; (3) the evaluation and selection indicators, such as learning abilities or innovative abilities, are difficult to quantify; and (4) the factors influencing cooperation among team members are difficult to define, possibly leading to a lack of trust or conflicts between different personalities.

No study has developed a complete virtual team formation approach designed for offering knowledge-based service in knowledge markets. This study proposes a knowledge service team formation approach. The main tasks were designing (1) a role selection method, which involved proposing a method for establishing professional roles for knowledge service teams according to the knowledge service requirement statement of the knowledge service requesters; (2) a method for evaluating knowledge service team members, which entailed designing an evaluation index model that consists of five major dimensions according to dispersed, dynamic, and timely properties; and (3) a team combination method, which involved establishing a team combination model according to the result of the team combination index and goal definition.

Finally, a system for verifying the aforementioned methods was implemented. A virtual knowledge service team that possesses both individual abilities and team cohesiveness could be established effectively through this study, allowing teams to achieve high performance and to provide knowledge requesters with optimal knowledge service.

2. RELATED STUDIES

In the knowledge-based industry environment, knowledge workers are usually engaged in knowledge-related tasks such as product development. Knowledge workers know how to use old knowledge by reapplying and repackaging it to generate new knowledge (Davenport, Jarvenpaa, & Beers, 1996) or supporting their execution of tasks (Liu, Lin, & Chen, 2013). Knowledge workers are mainly responsible for tasks involving brain activities (Stewart, 1997), transforming existing knowledge into valued products, and solving problems with their expertise through services (Horibe, 1999; Miller, 1998).

A virtual team is composed of workers in different organizations with a shared purpose across space (Agustin-Blas et al., 2011; Dodson et al., 2010; D'Souza & Colarelli, 2010). Team members rarely complete endowed tasks through face-to-face communication, possibly because of time or geographical dispersion factors (Lipnack & Stamps, 1999). Virtual team members can overcome the distance, time, and space boundaries of organization, as well as cultural differences, to accomplish a specific team goal by using electronic communication and digital technologies (Maznevski & Chudoba, 2000).

By integrating virtual team discussions from researchers (Dodson et al., 2010; Love & Roper, 2009; Maznevski & Chudoba, 2000), this study defines a virtual knowledge service team as a group of knowledge workers dispersed among various locations, organizations, or even countries who use their expertise (knowledge, technologies, and abilities) to accomplish a common goal by working mutually across space and time through the internet and information technologies. The characteristics of virtual knowledge service team members derived from the study were: (1) sharing common goals; (2) possessing distinct professional abilities; (3) having culturally diverse backgrounds; (4) being geographically dispersed; and (5) communicating through information technology.

Adequate member selection and combination could facilitate a highly efficient knowledge service team. Relevant literature has primarily evaluated team efficiency from two aspects: (1) final result yielded, such as the quantity and quality of the products; and (2) team member satisfaction (Hackman, 1983). Based on the two dimensions of team efficiency, researchers have proposed the factors influencing team efficiency successively. The characteristics of team members include mutual commitment, mutual support, mutual responsibility, and openness and flexibility to manage contingency (Wi, Mun, Oh, & Jung, 2009; Wysocki, Beck, & Crane, 2000). Four factors affecting virtual team performance are team factors, task properties, environmental factors, and technological factors. Based on previous studies, this study concluded that the factors influencing team efficiency include the characteristics of team members, structure of a team, organizational environment, and task characteristics.

Yoo and Alave (2004) stated that the primary criteria for team member selection are knowledge and abilities. Chung and Guinan (1994) believed that team members should be experienced. More experienced teams usually perform more effectively than teams lacking experience, and ability is an element essential to incorporating knowledge fully. Moreover, a high-quality team generally consists of team members with different abilities (Haque, Pawar, & Barson, 2000). However, language differences could cause communication difficulties when each team member originates from different countries. Thus, team performance could also be influenced by communication among team members (Blackburn, Furst, & Rosen, 2003).

Exploring personality traits involves unique and continuous behaviors consistently performed by human beings in different situations (Costa & McCrae, 1992; Funder, 2001), which is one of the factors influencing team performance (Zakarian & Kusiak, 1999). Managers who effectively use workers with different traits improve the performance of individuals in a team and contribute greatly to team performance (Trower & Moore, 1996, April). Moreover, trust among team members has a substantial effect on virtual teams that are particularly concerned about rapid assembly and dismissal (Coutu, 1998; Dayan & Benedetto, 2010; Saonee, Joseph, & Suprateek, 2000).

The strength and weakness of knowledge workers are the primary considerations for team combination. The higher the cohesiveness is among team members, the more effective the performance of a team (Chen & Lin, 2004). The cooperation of the team is facilitated when the team members mutually trust one another (Coutu, 1998), and the most direct approach to judging trust among team members is mutual evaluation between two team members. Considering factors other than mutual evaluation is necessary for enhancing the evaluation of cohesiveness (Gordon, Mondy, Sharplin, & Premeaux, 1990). When the personalities of the team members match each other, conflicts are reduced and negotiation between team members is enhanced (Chen & Lin, 2004).

3. EVALUATION AND SELECTION INDICATOR ESTABLISHMENT

First, this section introduces the evaluation indicators used in the study during the member selection and team combination stages of establishing a team.

- **Member Evaluation and Selection Indicators:** According to the discussion on the characteristics of team members in Section 2, this study adopts the following five items as the evaluation indicators for team member selection:

(1) Reputation (*R*): Regarding relevant external evaluations for individuals or particular organizations, reputation is a perception of value. Overall, reputation is a type of qualitative expectation. In k-commerce, knowledge providers acquire evaluations from third parties in the following ways: (a) Knowledge providers obtain a buyer appraisal (R_1) after the transactions of knowledge products, such as patents, occur; and (b) when knowledge workers participate in projects, leading enterprises and other team partners provide the partner with a partner appraisal (R_2). This indicator is used to evaluate the reputation of knowledge workers according to these two forms of feedback.

(2) Knowledge (*K*): The most critical indicator for selecting the team members of a knowledge service is the degree of knowledge held by the knowledge workers, and experience is the process of knowledge accumulation. This study examined the knowledge of knowledge workers according to the knowledge of products (K_1) and project experience (K_2).

(3) Basic ability (*BA*): According to the basic ability for working and the ability structure for knowledge workers defined by the Secretary's Commission on Adopting Necessary Skills (SCANS), United States, adaptability ability (BA_1), practice ability (BA_2), learned ability (BA_3), organization ability (BA_4), innovation ability (BA_5), and decision ability (BA_6) could be adopted to examine the basic abilities of knowledge workers.

(4) Long-range cooperative ability (*CA*): Knowledge service teams belong to highly virtualized organizations; therefore, in addition to basic abilities, knowledge workers are required to have long-range cooperative abilities. Long-range cooperative ability comprises self-management (CA_1), language ability (CA_2), and information intensity (CA_3) (Blackburn et al., 2003).

(5) Personality specialty (*PS*): To investigate the unique and continuous behaviors consistently performed by human beings in different situations (Costa & McCrae, 1992; Funder, 2001), researchers have categorized personality specialty into different classifications. However, the "big five personality traits" are the personality traits that are most widely used, and are supported by strong verifications (Bozionelos, 2004). The big five personality traits are mood stability (PS_1), openness (PS_2), rigor (PS_3), friendliness (PS_4), and extroversion (PS_5). This study adopted the big five personality traits as specialty indicators of personality to evaluate knowledge workers (Costa & McCrae, 1992; Eysenck & Eysenck, 1975; Norman, 1963).

- **Team Combination Indicators:** Conflicts are reduced and negotiation between team members is enhanced when members' personalities match (Chen & Lin, 2004). When there is high cohesiveness and mutual trust among team members, pleasure is present during cooperation, thereby increasing team performance (Chen & Lin, 2004; Coutu, 1998). The most direct method for measuring mutual trust is to evaluate team members who have cooperated previously. However, unfavorable evaluation can be induced when members are not acquainted with each other or do not have opportunities to interact directly in virtual knowledge service teams. Thus, other factors, such as the Myers-Briggs Type Indicator (MBTI), should be considered exclusive from mutual evaluation to enhance the evaluation of team member cohesiveness. To increase the cooperative cohesiveness among team members, this study incorporated the MBTI into a factor to examine team member cohesiveness. The MBTI can cause individuals to understand their own strengths and weaknesses, and the complementarities among team partners are understood (Tomal, 1992). The MBTI is suitable for cohesiveness evaluation among team members. The MBTI is a personality test containing four dichotomies; each dichotomy has two preferences (Moody, 1988): (1) the trend for mental ability, dichotomized into extroversion (*E*) and introversion (*I*); (2) the way to understand the external world, divided into sense (*S*) and intuition (*N*); (3) the way for decision making, divided into thinking (*T*) and feeling (*F*); and (4) the way of living and attitude towards performing actions, divided into judging (*J*) and perceiving (*P*). The indicators for team combination established in this study are individual ability, mutual appraisal, and the MBTI compatibility degree.

4. VIRTUAL KNOWLEDGE SERVICE TEAM FORMATION METHOD

According to the virtual team life cycle (Furst, Reeves, Rosen, & Blackburn, 2004) and studies on team formation (D'Souza & Colarelli, 2010; Wi et al., 2011), goal setting, and human resource selection are considered the primary tasks in the team formation stage that allow the team to develop smoothly. This section presents a designed three-phase virtual knowledge service team formation model (Figures 1):

(1) Role selection phase: Selecting authoritative experts with conformed professional backgrounds is necessary for establishing decision groups according to the demand of knowledge requesters. The main task for a decision group is to transform the demands of the knowledge requester into specific and clear roles according to demand, including a specific role name, role professional field, role specialty, and population of each role. The subsequent step involves comparing role demands and knowledge-worker-related characteristics and selecting knowledge workers who match the role demands as the candidates. The characteristic information of knowledge workers comprises three dimensions: (1) knowledge product, including product name, field, time, value, and buyer appraisal value; (2) specialty; and (3) project experience, including project field, name, time, cost, assigned role, and partner appraisal value.

(2) Team member selection phase: The selection of team members is a crucial step in developing effective virtual teams (D'Souza & Colarelli, 2010). After roles are selected, each role may have more than one candidate. This phase involves selecting the competent knowledge workers according to the big five selection indicators. Accordingly, phase selection matches the weight value for each indicator established from expert decision-making groups and provides an overall evaluation of knowledge workers according to a fuzzy aggregation operator and composite index.

(3) Team combination phase: The overall performance of the team can be influenced by whether team members interact harmoniously. Therefore, the purpose of this phase is to select members with high cohesiveness based on the cooperative relationships among members to establish an optimal virtual knowledge service team.

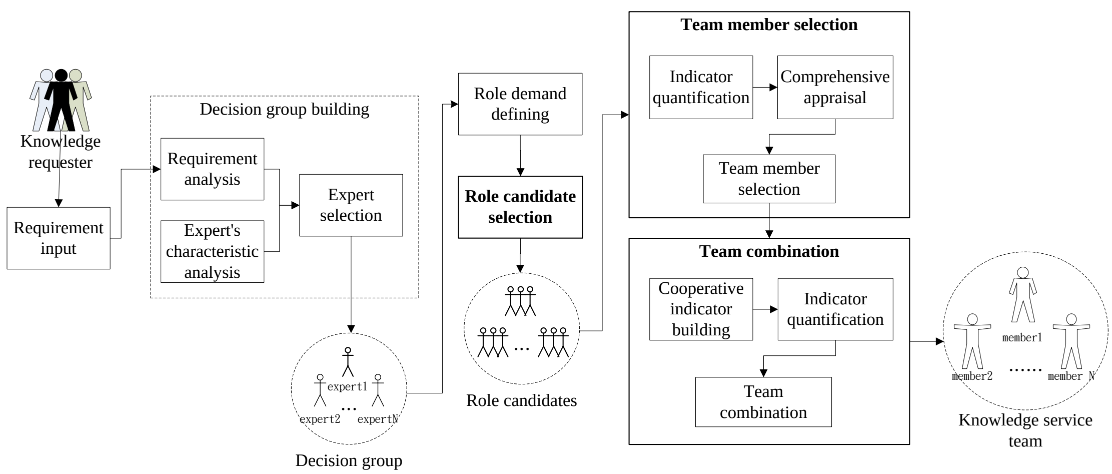


Figure 1 Virtual knowledge service team formation model

4.1 Role Selection Method

4.1.1 Role Evaluation and Selection Procedure

This section presents the design of a role evaluation and selection procedure (Figure 2). First, a decision group composed of experts assists in establishing categories of expertise roles in the knowledge service teams according to requesters' knowledge of service requirement statements and in establishing a role characteristics set for required roles, including the name, field, and specialties of the roles. Simultaneously, according to the personal profile of knowledge workers, the collective characteristics of knowledge workers related to role characteristics, including individual specialties, professional knowledge field, and project experience, are obtained from knowledge DB. Two collective characteristics are compared to identify similarities. If the similarity exceeds the threshold established by the decision group, then the knowledge worker becomes the candidate matching the basic conditions. The details of the characteristic similarity calculation are explained in the following subsection.

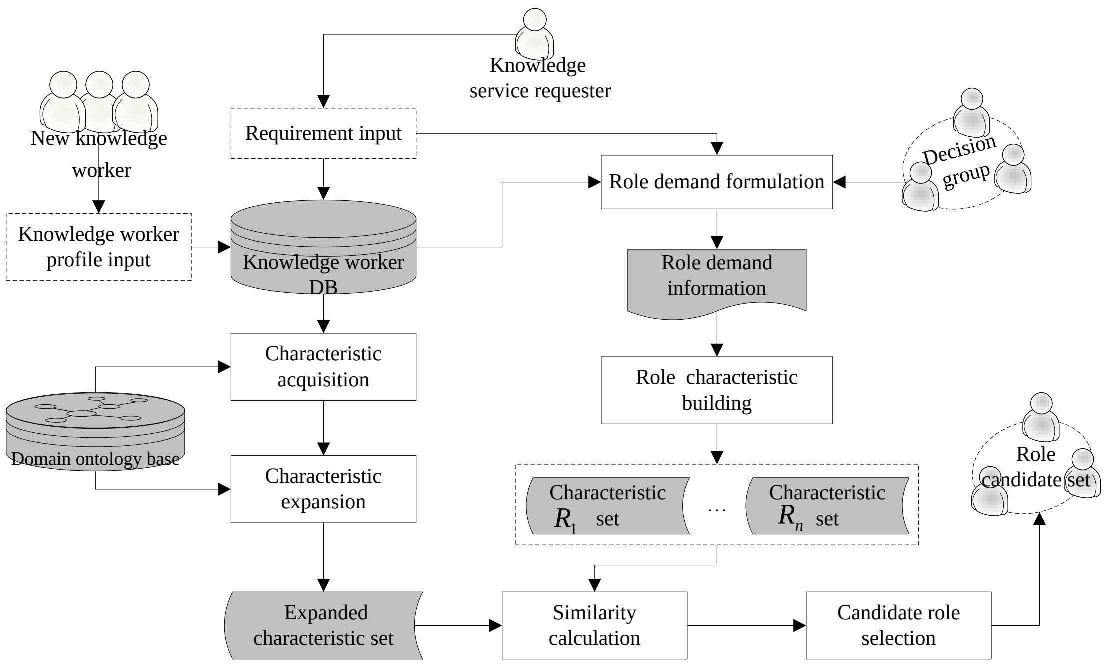


Figure 2 Role evaluation and selection procedure

4.1.2 Characteristic Similarity Calculation

Decision groups can establish their weight values according to the significance of the collective concepts after expansions, causing the similarity calculation result to further match the users' intentions. This study adopted the Jaccard coefficient to conduct similarity matching (Guha, Rastogi, & Shim, 1998), which involves transforming the two sets of characteristics into vectors. Assuming that $A_i = \{c_1, c_2, c_3, \cdots, c_p\}$ is the characteristic set for expert roles (R_i) and $B_j = \{c_1, c_2, c_3, \cdots, c_p\}$ is the characteristic set for knowledge workers (K_j) after expansion, similarity matching is shown as follows:

(1) Subclass for knowledge worker establishment: To prevent excessive numbers of characteristics from influencing the accuracy of similarities, the non-related characteristics of K_j and R_i should be removed to obtain the subclass E_{ij} of the characteristics K_j.

(2) Vector space model establishment: According to the significance of the characteristics, each characteristic in the set must be assigned a weight value. Therefore, the role characteristic vector $\overrightarrow{A_i} = \{V_1^{A_i}, \cdots, V_p^{A_i}\}$ and knowledge worker $\overrightarrow{E_{ij}} = \{V_1^{E_{ij}}, \cdots, V_p^{E_{ij}}\}$ characteristic vector are obtained.

(3) Similarity Analysis: Similarity analysis was conducted using the Jaccard coefficient (F.1). A larger value represents a higher similarity between two vectors, indicating that the knowledge worker is more suited to the role. Conversely, a smaller value indicates that the candidate is less suited to the role.

$$sim(\overrightarrow{A_i}, \overrightarrow{E_{ij}}) = \frac{\sum_{k=1}^{p}(V_k^{A_i} \times V_k^{E_{ij}})}{\sum_{k=1}^{p}(V_k^{A_i})^2 + \sum_{k=1}^{p}(V_k^{E_{ij}})^2 - \sum_{k=1}^{p}(V_k^{A_i} \times V_k^{E_{ij}})} \tag{F.1}$$

(4) Role Selection: The decision group determines the threshold (α). Higher accuracy can be obtained by adjusting the threshold to a higher standard when more candidates are considered. The knowledge worker is selected to perform the role when the similarity between the role and knowledge worker is greater than α.

4.2 Virtual Team Member Selection Method

First, the decision group selects the evaluation indicators considered for role selection according to the characteristics and professional requirements of each role in the team. Most of the evaluation indicators are qualitative indicators; this section presents a proposed method used for quantifying the evaluation indicators of knowledge worker candidates. Experts of decision groups have different views on the significance of each indicator. This section presents a design of the method for calculating the weight values of evaluation indicators and integrating the weight value of an evaluation indicator of a decision group. Finally, a weighted aggregate evaluation is conducted to allow the obtained value to adequately represent the overall evaluation of the knowledge workers. The detailed method is described as follows.

4.2.1 Design of Indicator Quantification Methods

Indicator quantification is the process of transforming evaluation indicator scales into numbers. This subsection shows the design of an adequate quantification method according to the team member selection indicators in Section 3.

(1) Reputation quantification: This study evaluated the reputation of knowledge workers based on the appraisals of buyers and partners (also called appraisers). Based on human thinking patterns, a five-scale linguistic variable (very poor, poor, fair, good, and very good) was adopted to express feelings on the degree of reputation (Chen & Hwang, 1992). To allow qualitative evaluation to be used to evaluate knowledge workers' reputations, the following three steps were performed in quantifying the reputation of knowledge workers:

1) **Establishing fuzzy appraisal values:** The linguistic variable is transformed into fuzzy evaluation values though the fuzzy values established in the previously designed linguistic scales (Table 1).

Table 1 Linguistic variables and their ranges

The Value of Linguistic Variable	**Code Name**	**Fuzzy Preference Value**
Very Poor	VP	(0, 0, 0.25)
Poor	P	(0, 0.25, 0.5)
Fair	F	(0.25, 0.5, 0.75)
Good	G	(0.5, 0.75, 1)
Very Good	VG	(0.75, 1, 1)

2) **Integrating fuzzy appraisal values:** After single appraisal values are transformed into fuzzy appraisal values, overall comments from the appraisers are integrated. To prevent extreme values from influencing the integrated results, this study adopted the geometric mean method proposed by Ishikawa (1993) in conducting an integrated operation to obtain an adequately representative appraisal value. The method is shown in F.2-F.5:

$$\tilde{w}_k = (a_k, b_k, c_k),\ \ 1 \le k \le n, \tag{F.2}$$

where $\tilde{w}_k$ is the k^{th} fuzzy appraisal value of the knowledge worker; a_k, b_k, and c_k are the left, midpoint, and right end points of the triangle membership function of the k^{th} appraisal, respectively; and n is the total number of all appraisals of the knowledge worker.

$$\alpha = Min\{a_k\}, \tag{F.3}$$

$$\beta = \sqrt[n]{\prod_{i=1}^{n} b_k}, \tag{F.4}$$

$$\gamma = Max\{c_k\}, \tag{F.5}$$

where α, β, and γ are the minimum left end value, geometric mean of the vertex, and maximum right end point of the triangle membership function of all appraisals of the knowledge worker, respectively.

3) **Defuzzification:** Finally, this study adopted the center of gravity method (F.6) to transform fuzzy values into a clear and definite reputation value (R) that represents the overall appraisal value.

$$R = \frac{\alpha + \beta + \gamma}{3} \quad . \tag{F.6}$$

These steps are performed to transform the linguistic value of knowledge workers into corresponding reputation values. For example, a knowledge worker (Dr. John) obtained three appraisals from the purchasers, G, VG, and F. These values were transformed into geometric fuzzy values (0.5, 0.75, 1), (0.75, 1, 1), and (0.25, 0.5, 0.75), respectively, in advance in Table 1. Subsequently, α = 0.25, β = 0.72, and γ = 1 were obtained using F.3 to F.5. Finally, Dr. John's reputation value calculated from F.6 was 0.66.

(2) **Knowledge degree quantification:** This study considered that the expertise of knowledge workers can be evaluated through possessed knowledge products as well as participatory project experiences. The quantification methods are shown in the following:

- **Knowledge product quantification:** In addition, the quantity and quality of a knowledge product that a knowledge worker possesses could affect his or her knowledge level. The quality of a knowledge product can be evaluated according to the value of use and the commercial benefit of knowledge. The value of knowledge evolves over time; therefore, time is a key factor that influences the value of knowledge. Newer knowledge often provides a greater contribution to the knowledge degree of knowledge workers than older knowledge does. This study designed the following contribution value (K_1) quantification method for evaluating the knowledge degree of knowledge workers:

$$K_1 = \sum_{i=1}^{m} \frac{1}{t_c - t_i + 1} \times V_i, \tag{F.7}$$

where m is the total number of knowledge products belonging to a knowledge worker; t_c is the current time (yyyy); and t_i and V_i are the year of manufacture and value of the i^{th} knowledge product of the knowledge worker, respectively.

- **Project experience quantification:** This study adopted the project experience value to evaluate the knowledge degree of knowledge work, number of times of participating in projects, and difficulties of the projects, because these factors can influence the project experience value. The difficulty of projects can be evaluated according to the sum of the amount of equipment invested and human resource costs. The closer to the time a worker participated in a project is, the greater the contribution value of the knowledge of the knowledge worker. To evaluate the effect of a project level on a knowledge worker's project experience, this study adopted a relative comparison. The method involved choosing the lowest and highest project experience boundary values of the total investment cost and proposing a method to quantify the project experience value (K_2) of the knowledge worker:

$$K_2 = \sum_{j=1}^{n} \frac{1}{t_c - t_j + 1} \times \left(\frac{m_j - m_l}{m_h - m_l} + 1 \right), \tag{F.8}$$

where n is the total number accumulated for the projects in which a knowledge worker participated; t_c is the current time (yyyy); t_j and m_j are the starting year and total investment cost of the j^{th} project in which the knowledge worker participated, respectively; and m_h and m_l are the maximum and minimum values of the total investment cost for the participatory project experiences of all candidate knowledge workers, respectively.

(3) Basic ability quantification: Basic ability (BA) comprises six ability indicators (BA_1 - BA_6), as described in Subsection 3.1. Basic ability is identical to long-range cooperation ability and is an abstract concept that is difficult to quantify. The following method for quantifying long-range cooperation ability could be used as the basic ability quantification method.

(4) Long-range cooperation ability quantification: Long-range cooperation ability is composed of three indictors that are difficult to quantify: degree of informatization, self-management ability, and language ability. To solve this problem, this study used tests to evaluate the ability of knowledge workers. Numerous items regarding ability must be evaluated. The test can be simplified when conducted as a self-appraisal, but the trustworthiness of self-appraisal is often low. Therefore, this study adopted an external appraisal for adjusting self-appraisal to enhance public trust. In k-commerce, the information for external appraisal is derived from "buyer appraisal" (R_1) and "partner appraisal" (R_2) under "reputation" (R). This study designed the following method for quantifying the long-range cooperation ability value (*CA*) of knowledge workers:

$$CA = AO + (\frac{R_1 + R_2}{2} - 0.5) \times AO, \tag{F.9}$$

where AO is the self-appraisal value of a knowledge worker, $0 \le AO \le 10$; and R_2 and R_1 are quantified values of buyer and partner appraisals of the knowledge worker's products, respectively.

(5) Personality specialty quantification: This study adopted a personality traits test, the NEO–Five Factor Inventory (NEO-FFI; Costa and McCrae, 1992), to quantify personality specialties. The scores range from 5 (complete match) to 1 (poor match). Thus, the total score for the personality test falls between 12 and 60. A higher score represents more significant characteristics.

4.2.2 Design of Indicator Weight Calculation

The analytic hierarchy process (AHP) is used to compare evaluation criteria in pairs, allowing decision makers to conduct a fair and balanced evaluation among various criteria (Saaty, 1980). This method can lead to a great load for decision makers, and a consistency test should be completed after establishment. The simplest method for calculating weight values is calculating the mean, but the consensus problem for weighting the indicators is not considered for decision makers. Therefore, this study adopted the fuzzy aggregation operator proposed by Shen and Hsieh (2006). The fuzzy aggregation operator is easy to calculate and accounts for the average strength and consistency between experts. Moreover, the indicators of this study were built on a hierarchical structure. Therefore, this study added a series of hierarchies to the fuzzy aggregation operator to calculate weight values. The main steps are described as follows:

(1) Establishing an indicator evaluation matrix: To provide an easy explanation, this study assumed that there are *m* experts and *n* indicators, in which the maximum degree of significance for each indicator is the ideal value represented by I_j. The experts provide a significant evaluation value y_{ij} to each indicator and establish an evaluation matrix, *Y*, according to all the values obtained, as shown in F.10:

$$\mathrm{Y}=[y_{ij}]=\begin{bmatrix} y_{11} & y_{21} & \cdots & y_{m1} \\ y_{12} & y_{22} & \cdots & y_{m2} \\ \vdots & & \cdots\cdots & \vdots \\ y_{1n} & y_{2n} & \cdots & y_{mn} \end{bmatrix} \quad 1 \le i \le m,\ 1 \le j \le n, \tag{F.10}$$

where y_{ij} is the significance evaluation value of the i^{th} expert to the j^{th} indicator.

(2) **Calculating the degree of membership (μ_{ij}) on the ideal value (I_j) of distance y_{ij} in the evaluation matrix:** Dividing each actual evaluation value in a specific indicator (y_{ij}) by the ideal value (I_j) yields the membership for the ideal point of each point distance (μ_{ij}), as shown in F. 11:

$$\mu_{ij}=\frac{y_{ij}}{I_j}\ . \tag{F.11}$$

(3) **Calculating the harmonic mean (h_j) of the membership for each indictor *j*:**

$$h_j=\frac{1}{m}\sum_{i=1}^{m}\frac{1}{\mu_{ij}}\ . \tag{F.12}$$

(4) **Calculating the strength of the weight intensity (e_j) of each indicator j:**

$$e_j=\frac{1}{h_j}\ . \tag{F.13}$$

(5) **Calculating the average weight intensity (w_j) for each indicator:**

$$w_j=\frac{e_j}{\sum_{j=1}^{n}e_j}\times 100\%\,. \tag{F.14}$$

(6) **Calculating the overall weight value:** After calculating the weight value for each evaluation indicator, a series of hierarchies is implemented to calculate the overall weight value. The method involves multiplying the weight of the bottom most indicator j, w_{kj}, by a level of the weight of the related indicator, w_k. When the multiplication reaches the top hierarchy, the obtained value represents the total weight value of this particular indicator j.

The calculation method is shown as follows:

$$w_j = w_k \times w_{kj} \,. \tag{F.15}$$

4.2.3 Design of a Comprehensive Fitness Evaluation Method

This subsection presents an integrated evaluation of knowledge workers that combines the quantified values of each indicator and the overall weighted values that are calculated. High-quality knowledge worker candidates are evaluated and selected from a large group of candidates to form a knowledge service team. The measurement range of the value for each evaluated indicator is not identical. This study adopted a synthetic index to normalize the evaluation of the knowledge worker’s value for each indicator to prevent deviation that influences the evaluation and selection results caused by a specific index evaluation. The synthetic index also combines the weighted values of indicators, and a weighted average is evaluated by incorporating the selected fitness of the knowledge workers. The steps are shown as follows:

(1) Establishing a decision-making evaluation matrix: According to the quantified evaluation value possessed by knowledge worker candidates, a decision-making evaluation matrix involving all knowledge worker candidates and evaluation indicators is established. Assuming that there are m knowledge workers and n indicators, the decision-making evaluation matrix B is shown in F. 16:

$$B = [x_{ij}] = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{m1} \\ x_{12} & x_{22} & \cdots & x_{m2} \\ \vdots & & \cdots\cdots & \vdots \\ x_{1n} & x_{2n} & \cdots & x_{mn} \end{bmatrix} \qquad 1 \le i \le m,\ 1 \le j \le n, \tag{F.16}$$

where x_{ij} is the evaluation value of the j^{th} indicator of the i^{th} knowledge worker.

(2) Normalization of the decision-making evaluation matrix: The evaluation value should be normalized for comparison because of the irregular range of scores. The formula is shown in F. 17:

$$Y_{ij} = \frac{x_{ij}}{\frac{1}{m}\sum_{i=1}^{m} x_{ij}} \quad , \tag{F.17}$$

Where Y_{ij} is the evaluation value of the j^{th} indicator of the i^{th} knowledge worker after normalization.

The decision-making matrix after normalization B' is

$$B' = [Y_{ij}] = \begin{bmatrix} Y_{11} & Y_{21} & \cdots & Y_{m1} \\ Y_{12} & Y_{22} & \cdots & Y_{m2} \\ \vdots & & \cdots\cdots & \vdots \\ Y_{1n} & Y_{2n} & \cdots & Y_{mn} \end{bmatrix} \tag{F.18}$$

(3) Calculating the weight aggregate index:

$$Y_i = \sum_{j=1}^{n} w_j Y_{ij} \, , \tag{F.19}$$

where Y_i is the evaluation value of the i^{th} knowledge worker's overall ability; and w_j is the overall weight value for the j^{th} indicator.

Finally, arrange the obtained overall ability evaluation value (Y_i) in order. A larger Y_i represents greater individual ability.

4.3. Team Combination Method

This section presents the design of a team combination algorithm applied to forming a knowledge service team with high abilities and cohesiveness. This algorithm is established according to the team combination indicators mentioned in Section 3.

4.3.1 Design of a Genetic Algorithm-based Team Combination Algorithm

Based on the team combination indicators and role demand and constraints established by a decision group, including the number of workers required for each role and the strength of cooperation, the team combination is a search for a maximized combination problem involving multiple criteria. This study proposes a team combination algorithm based on the genetic algorithm (GA; Hwang ,Yin, Hwang, & Tsai, 2008). First, a goal function is established (F.20) that indicates that the overall team abilities and cohesiveness should be maximized. The constraint function F.21 represents the number of people limited for each demanded role.

$$Max \quad Z = \sum_{i=1}^{k} \sum_{j=1}^{P_i} \sum_{i'=i}^{k} \sum_{j'=1}^{P_i'} \alpha_{ii'} \left[w\left(I_{ij} + I_{i'j'}\right) + \left(1-w\right)\left(A_{ij\to i'j'} + A_{i'j'\to ij} + S_{ij\leftrightarrow i'j'}\right)\right] p_{ij}\, p_{i'j'} \tag{F.20}$$

Subject to

$$\sum_{j=1}^{P_i} P_{ij} = PN_i \ , \ 1 \le i \le k \quad , \tag{F.21}$$

where Z is the target value; k is the number of roles types; p_i is the number of knowledge worker candidates for the i^{th} role; p_{ij} is the j^{th} knowledge worker belonging to the i^{th} role; 1 indicates that the candidate was selected for the role, whereas 0 indicates that the candidate was not selected ; PN_i is the number of knowledge workers demanded for the i^{th} role; $\alpha_{ii'}$ is the strength of the cooperative relationship between role i and i', $i \neq i'$; w is the weight value for the individual ability of the team members; $1-w$ is the weight value for the cohesiveness between two members; I_{ij} is the ability value for the j^{th} knowledge worker in the i^{th} role; $A_{ij \to i'j'}$ is the evaluation value for the j^{th} knowledge worker belonging to the i^{th} role to the j'^{th} knowledge worker belonging to the i'^{th} role, $i \neq i'$, $j \neq j'$; $A_{i'j' \to ij}$ is the evaluation value for the j'^{th} knowledge worker belonging to the i'^{th} role to the j^{th} knowledge worker belonging to the i^{th} role; and $S_{ij \leftrightarrow i'j'}$ is the personality trait cohesiveness between the j^{th} knowledge worker belonging to the i^{th} role and the j'^{th} knowledge worker belonging to the i'^{th} role.

The steps of the GA-based team combination algorithm are shown below:

(1) Establishing the fitness function: The fitness function can be used to judge the quality of chromosomes to calculate the foundation of the fitness value. Candidates with higher fitness values tend to have a higher probability of surviving and reproducing offspring. This study adopted the function (F.20) as the fitness function.

(2) Encoding method determination: This study adopted binary coding for chromosome design. Each gene represents a role, and the number of bits for each gene is determined according to the number of roles. Each bit indicates a candidate. The bit value is 1 when the candidate is selected, whereas the bit value is 0 when the candidate is not selected.

(3) Random generation of the initial group: A set of feasible solutions is yielded randomly according to the requirements of questions involving the initial group. Figure 3 shows an example in which role R_2 and R_3 require two knowledge workers each, whereas role R_1

and role R_4 only demand one knowledge worker. A feasible solution is yielded randomly by selecting the demanded number of people from the six candidates under each role category (Figure 3).

R_1	R_2	R_3	R_4
100000	001010	001010	100000

Figure 3 Diagram for the initial chromosome created

(4) **Selection**: This study adopted tournament selection, which was completed by randomly selecting a few candidates, and subsequently selecting the candidate with the maximum fitness value to reproduce offspring.

(5) **Crossover**: This study adopted a two-point crossover, randomly selecting two crossover points and exchanging the genes between these two crossover points to produce offspring.

(6) **Mutation**: To allow the mutated chromosomes to satisfy the constraint function (F.22), this study selected a gene for mutation. The method is used for exchanging two bit values selected in the genes to reproduce a new generation.

(7) **Establishment of termination criteria:** This study adopted the most common method to set a fixed algebra as the termination criteria.

4.3.2 Example Explanation

Assuming that a knowledge service team established by the decision group requires three different roles (R_1, R_2, and R_3), R_1 and R_2 require one knowledge worker each, whereas R_3 requires three knowledge workers. The strength values of the cooperative relationships among these roles were $\alpha_{12} = 0.3$, $\alpha_{13} = 0.4$, $\alpha_{23} = 0.5$, and $\alpha_{33} = 0.8$. The individual ability and cohesiveness indicator weight values were both 0.5. This study also assumed that there were five candidates for both R_1 and R_2, whereas there were eight candidates for R_3. The related information is illustrated in Tables 2-4.

Table 2 Individual ability values of knowledge worker

Role	R_1					R_2					R_3							
Knowledge worker	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{21}	P_{22}	P_{23}	P_{24}	P_{25}	P_{31}	P_{32}	P_{33}	P_{34}	P_{35}	P_{36}	P_{37}	P_{38}
Individual ability value	0.9113	1.1136	0.8843	0.916	1.1652	1.102	1.0475	0.8792	1.0847	0.8771	1.1114	0.9756	0.9589	0.9151	0.9206	0.9286	1.2329	0.9417

Table 3 Mutual appraisal values for knowledge worker

	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{21}	P_{22}	P_{23}	P_{24}	P_{25}	P_{31}	P_{32}	P_{33}	P_{34}	P_{35}	P_{36}	P_{37}	P_{38}
P_{11}	--	0.5	0.5	0.5	0.5	0.75	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.75	0.5
P_{12}	0.5	--	0.5	0.5	0.5	0.5	0.5	0.9167	0.5	0.5	0.75	0.5	0.75	0.5	0.5	0.5	0.5	0.9167
P_{13}	0.5	0.5	--	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.75	0.5	0.5	0.75	0.5	0.5
P_{14}	0.5	0.5	0.5	--	0.5	0.5	0.75	0.5	0.75	0.75	0.5	0.5	0.75	0.9167	0.5	0.5	0.5	0.9167
P_{15}	0.5	0.5	0.5	0.5	--	0.5	0.9167	0.5	0.5	0.5	0.7887	0.75	0.5	0.5	0.5	0.5	0.5	0.5
P_{21}	0.75	0.5	0.5	0.5	0.5	--	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.9167	0.5
P_{22}	0.5	0.5	0.5	0.75	0.75	0.5	--	0.5	0.5	0.5	0.75	0.9167	0.5	0.5	0.5	0.5	0.5	0.5
P_{23}	0.5	0.75	0.5	0.5	0.5	0.5	0.5	--	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.75
P_{24}	0.5	0.5	0.5	0.75	0.5	0.5	0.5	0.5	--	0.5	0.5	0.9167	0.5	0.5	0.9167	0.75	0.5	0.75
P_{25}	0.5	0.5	0.5	0.75	0.5	0.5	0.5	0.5	0.5	--	0.5	0.5	0.75	0.9167	0.5	0.5	0.5	0.5
P_{31}	0.5	0.75	0.5	0.5	0.6524	0.5	0.9167	0.5	0.5	0.5	--	0.25	0.9167	0.5	0.5	0.5	0.5	0.5
P_{32}	0.5	0.5	0.9167	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.5	--	0.5	0.5	0.5	0.9167	0.5	0.5
P_{33}	0.5	0.75	0.5	0.75	0.75	0.5	0.75	0.5	0.5	0.9167	0.5	0.5	--	0.75	0.5	0.5	0.5	0.5
P_{34}	0.5	0.5	0.5	0.75	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.5	0.9167	--	0.5	0.5	0.5	0.5
P_{35}	0.25	0.5	0.5	0.25	0.5	0.75	0.5	0.5	0.9167	0.5	0.5	0.5	0.5	0.5	--	0.5	0.75	0.75
P_{36}	0.5	0.5	0.75	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.5	0.4777	0.5	0.5	0.5	--	0.5	0.5
P_{37}	0.75	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	--	0.75
P_{38}	0.5	0.75	0.5	0.75	0.5	0.5	0.5	0.75	0.9167	0.5	0.5	0.5	0.5	0.5	0.75	0.5	0.75	--

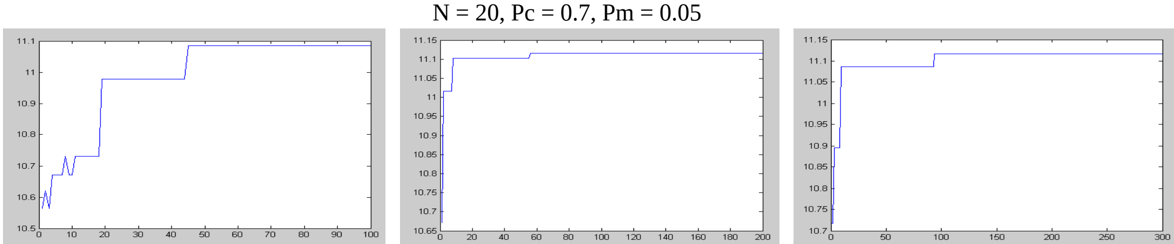
Table 4 Quantified values for the cohesiveness of the knowledge worker characteristics

	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	P_{21}	P_{22}	P_{23}	P_{24}	P_{25}	P_{31}	P_{32}	P_{33}	P_{34}	P_{35}	P_{36}	P_{37}	P_{38}
P_{11} (ENTP)	--																	
P_{12} (ENFJ)	0.5	--																
P_{13} (INFJ)	0.33	0.5	--															
P_{14} (ESTJ)	0.5	1	0.83	--														
P_{15} (ESTP)	0.83	0.67	0.5	0.33	--													
P_{21} (ISTP)	0.67	0.5	0.33	0.17	0.5	--												
P_{22} (ESTP)	0.83	0.67	0.5	0.33	0.67	0.5	--											
P_{23} (INFJ)	0.33	0.5	0.33	0.83	0.5	0.33	0.5	--										
P_{24} (ENTJ)	0.33	0.83	0.67	0.83	0.5	0.33	0.5	0.67	--									
P_{25} (ESTJ)	0.5	1	0.83	0.67	0.33	0.17	0.33	0.83	0.83	--								
P_{31} (ENFJ)	0.5	0.67	0.5	1	0.67	0.5	0.67	0.5	0.83	1	--							
P_{32} (ESTP)	0.83	0.67	0.5	0.33	0.67	0.5	0.67	0.5	0.5	0.33	0.67	--						
P_{33} (ENFJ)	0.5	0.67	0.5	1	0.67	0.5	0.67	0.5	0.83	1	0.67	0.67	--					
P_{34} (ESFP)	1	0.5	0.33	0.5	0.83	0.83	0.83	0.33	0.67	0.5	0.5	0.83	0.5	--				
P_{35} (ISTJ)	0.33	0.83	0.67	0.5	0.17	0	0.17	0.67	0.67	0.5	0.83	0.17	0.83	0.33	--			
P_{36} (INFP)	0.67	0.17	0	0.5	0.83	0.67	0.83	0	0.33	0.5	0.17	0.83	0.17	0.67	0.33	--		
P_{37} (ESFP)	1	0.5	0.33	0.5	0.83	0.67	0.83	0.33	0.67	0.5	0.5	0.83	0.5	0.67	0.33	0.67	--	
P_{38} (ENTJ)	0.33	0.83	0.67	0.83	0.5	0.33	0.5	0.67	0.67	0.83	0.83	0.5	0.83	0.67	0.67	0.33	0.67	--

Five knowledge workers were then selected to form a knowledge service team from the established candidates. This study adopted a GA to obtain the optimal solution. First, parameter settings, including number of generations (G), number of populations (N), crossover rate (P_c), and mutation rate (P_m), should be completed in advance. The setting of appropriate parameters should be performed according to the testing results and sensitivity analysis. A specific explanation is provided as follows:

(1) Generation Analysis: The number of generations was used as a variable and simulated using the parameters 100, 200, and 300. The simulation result in Figures 4(a) shows that the generation (G = 100) is small, allowing the algorithm to converge rapidly. However, its maximum fitness value (11.0859) was smaller than the maximum fitness value of the generations 200 and 300 (11.1158); therefore, an optimal knowledge service team could not be formed. Figures 4(b) and (c) indicate that convergence could be achieved and the optimal solution could be generated when the generation reproduction was 200. Therefore, this study set generation at 200 based on this analysis.

N = 20, Pc = 0.7, Pm = 0.05

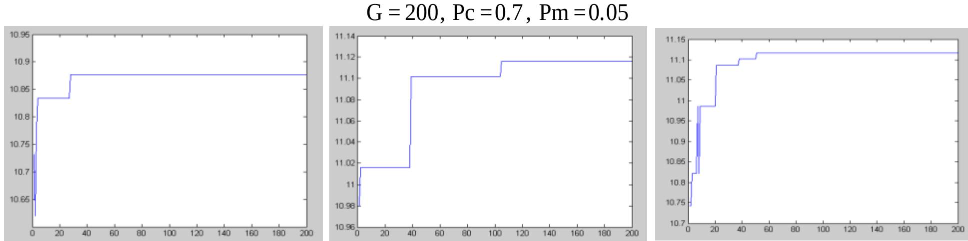


(a) (b) (c)

Figure 4 Sensitive analysis on generations

(2) Population analysis: The number of populations was adopted as a variable and was simulated using parameters 10, 20, and 30. The results are shown in Figure 5(a) and indicate that the population number was too small; therefore, an optimal solution could not be obtained. Figures 5(b) and (c) indicate that convergence and the optimal solution (11.1158) were achieved when the number of populations was 20 or 30. This study set the population number at 20 according to this analysis.

G = 200, Pc = 0.7, Pm = 0.05



(a) N=10 (b) N=20 (c) N=30

Figure 5 Sensitive analysis of population number

(3) **Analysis of crossover rate and mutation rate:** The crossover rate and mutation rate were used as variables for simulation. This study set the three crossover rate parameters at 0.5, 0.7, and 0.9, and the mutation rate parameters at 0.03, 0.05, and 0.08 to conduct a crossover experiment to seek an optimal combination. The results indicated that the mutation rate (P_m=0.03) may yield a premature convergence and fall into local optimization, whereas other crossover and mutation rate combinations could yield convergence and an optimal solution (11.1158). Difficulty for convergence occurred when both crossover (P_c=0.9) and mutation (P_m=0.08) rates were high. Convergence was achieved quickest when the crossover rate was P_c=0.7 and the mutation rate was P_m=0.05. This study set the crossover rate at 0.7 and mutation rate to 0.05 based on this analysis.

Finally, the calculation of genes was conducted using the set parameters (G=200, N=20, P_c=0.7, P_m=0.05) and terminat when the number of generations reached 200 and an optimal solution was obtained (fitness value: 11.1158, chromosome code: 010000001000001011), showing that a high-quality knowledge service team was formed by combining the candidates $[p_{12}\ p_{24}\ p_{35}\ p_{37}\ p_{38}]$.

5. CONCLUSION AND DISCUSSIONS

This section presents the implementation of a team formation system prototype according to the virtual knowledge service team formation method developed in this study. The equipment adopted for this prototype system was Microsoft Windows XP, Protégé 3.4, Apache HTTP Server Version 2.2, and MySQL 5.0.51a. The programming language adopted for system development was PHP 5.2.9.

The formation of an ERP software development project required by a small company is used as an example. According to interviews with experts in the software development domain, the following knowledge worker roles are required: (1) one project manager who has specialties in ERP, project management, and web-based system development technology; (2) one system analyst who has specialties in ERP, web-based system development technology, Java, Linux, and MySQL; and (3) three programming designers who have specialties in web-based system development technology, Java, Linux, and MySQL. Team combination was completed by inputting the information into the prototype system. Figure 6 shows the setting of role title, specialties, strength of role cooperation, and team combination factor weight values, and Figure 7 shows the different weight values provided by the experts according to personal comments.

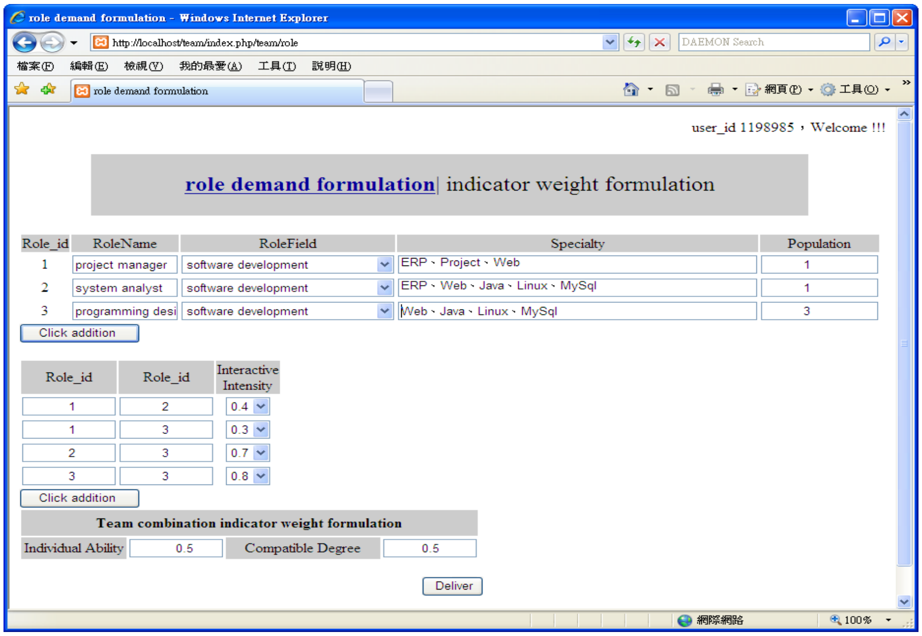


Figure 6 Role requirement input interface

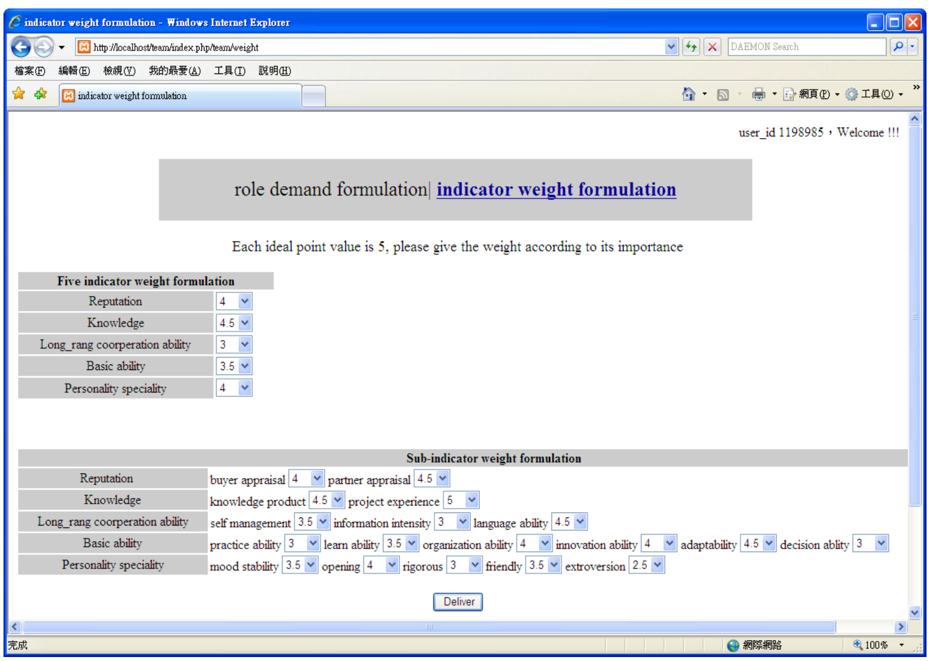


Figure 7 Indicator weight input interface

After calculation of the knowledge workers' individual abilities was complete, this study used the team combination method designed with the strength of role interaction and team combination indicator weights. This was used to establish a knowledge service team for which the results are shown in Figure 8. The system indicated the top three fitness values of the service team combination, providing selection opportunities for knowledge requesters.

Table 5 Candidate role list of knowledge workers

KW-ID	Similarity with R_1	Similarity with R_2	Similarity with R_3	Candidate role
1	1	0.4286	0.2859	R_1
2	1	0.4286	0.2859	R_1
3	1	0.4286	0.2859	R_1
4	1	0.4286	0.2859	R_1
5	1	0.4286	0.2859	R_1
6	0.6	1	0.8	R_2
7	0.3719	0.5556	0.4	elimination
8	0.6	1	0.8333	R_2
9	0.6	0.9942	0.8219	R_2
10	0.6	0.8571	0.6667	R_2
11	0.2	0.2857	0.1667	elimination
12	0.5785	0.9816	0.8099	R_2
13	0.4	0.7143	0.8333	R_3
14	0.4	0.7143	1	R_3
15	0.4	0.7143	1	R_3
16	0.4	0.6886	0.9859	R_3
17	0.4	0.7018	0.9932	R_3
18	0.4	0.7143	1	R_3
19	0.4	0.7143	1	R_3
20	0.4	0.7143	1	R_3

Table 6 Personal ability list of member

	R_1: Project Manager					R_2: System Analyst					R_3: Programmer							
KW-ID	1	2	3	4	5	6	8	9	10	12	13	14	15	16	17	18	19	20
Personal Ability	0.9113	1.1136	0.8843	0.916	1.1652	1.102	1.0475	0.8792	1.0847	0.8771	1.1114	0.9756	0.9589	0.9151	0.9206	0.9286	1.2329	0.9417

After calculation of the knowledge workers' individual abilities was complete, this study used the team combination method designed with the strength of role interaction and team combination indicator weights. This was used to establish a knowledge service team for which the results are shown in Figure 8. The system indicated the top three fitness values of the service team combination, providing selection opportunities for knowledge requesters.

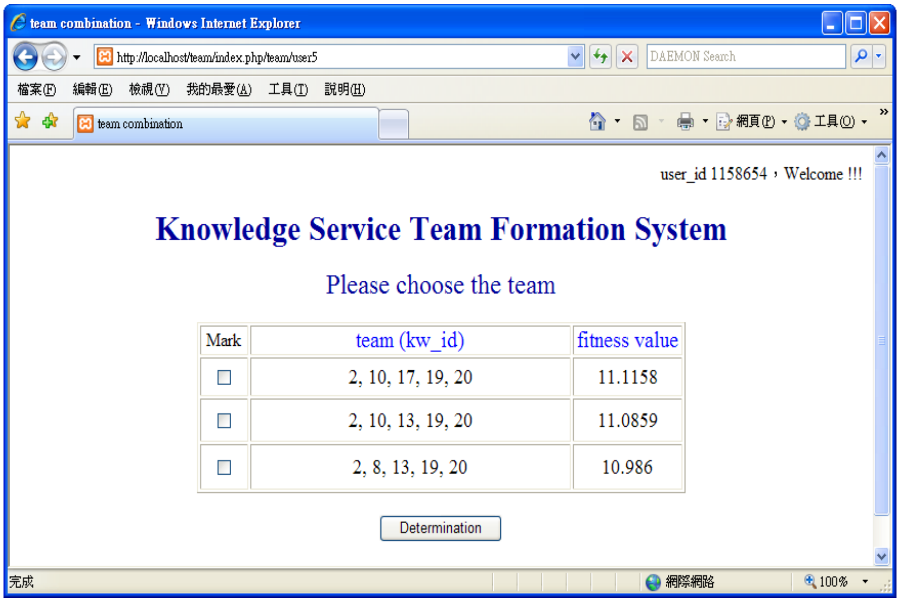


Figure 8 Result of knowledge service team combination

To provide knowledge requesters with an optimal knowledge service, this study proposes a method for virtual knowledge team formation in which the abilities of members and the cooperative relationships between team members and knowledge expert roles are considered. The knowledge-based service team formed by the members from different fields can solve diverse and complex problems.

The methods proposed in this study are (1) the decision method for roles. The candidates matching the role requirements can be determined by matching the similarity between roles and knowledge workers according to the requester's knowledge service requirement statement. (2) The selection and evaluation method for knowledge service teams was designed according to the dispersed, dynamic, and timely characteristics of the virtual team. The design involves the evaluation indicator model, which comprises five dimensions. (3) The method for combining the service team involves seeking the factor that influences the team by combining and defining the evaluation indicators and quantifying the method for each factor to develop an optimal method for service team combinations based on a GA.

Based on the implementation and testing of the systems, the method proposed in this study could be used to create a virtual knowledge service team according to the requirement statement; however, a limitation of the study is that locating a knowledge market already in operation for dynamic virtual team formation testing is difficult. The following directions are provided for future study: (1) The research effects should be applied and improved in knowledge service markets; (2) Because the decision group plays a critical role in the knowledge team formation process, an automatic and intelligent expert creating method should be established in the future; (3) Self-appraisal was adopted for abstract and unquantifiable indicators in the member ability evaluations; however, a more effective solution should be established in the future; and (4) To solve the appraisal problem between team members who do not have an opportunity to cooperate, a highly accurate and objective mutual appraisal that involves integration in social networks should be designed.

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