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Value ontology-based multi-aspect intellectual asset valuation method for decision-making support in k-commerce

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ABSTRACT

Advent of the innovation economy has ushered in knowledge as the most valuable corporate asset and a major impetus of product and service creativity. Knowledge commerce (k-commerce) refers to the real-time marketing and delivery of organizational knowledge via the Internet to enable knowledge to be transferred from owners to consumers legally and rapidly. In k-commerce, however, buyer cannot acquire complete product knowledge and can only rely on a limited description of product specifications and fragmented knowledge summary to make purchasing decisions. Consequently, a relatively objective method must be developed for automated knowledge valuation to provide a valuable reference for buyers and sellers, as well as ensure a functioning knowledge market. This study first analyzes the scenario for knowledge valuation activities in k-commerce to identify knowledge services in different knowledge-commercialized phases. A knowledge valuation factor model is then developed that comprises five aspects: knowledge inventor capability, knowledge supplier reputation, knowledge innovative degree, knowledge complexity and knowledge marketable value. To evaluate the market value of knowledge efficiently, a knowledge value ontology (KVO) is constructed based on historical product transaction records to offer the latest value and market status of similar knowledge. Based on factors in the knowledge valuation factor model, finally this study develops a multi-aspect knowledge valuation method including four evaluation sub-methods, capable of estimating the market value of knowledge products from different aspects. The proposed method allows for more rational and accurate decision making for the seller's pricing or the buyer's product selection, thereby encouraging market transactions by reducing information asymmetry and risks while enhancing fairness during a transaction.

1. Introduction

The significance of knowledge has increased for economic development, business management and even individuals, necessitating that individuals and businesses sustain their competitive edge through a quick acquisition of knowledge as an effective means of facilitating production, decision making and development of new knowledge (Bertino, Khan, Sandhu, & Thuraisingham, 2006; Bharadwaj & Tiwana, 2005). However, the lack of effective incentives and an absence of trust in human relations has made knowledge suppliers hesitant to offer core knowledge unselfishly. Moreover, in an era of stringent competition and knowledge explosion, knowledge between individuals can be shared effectively only through a market mechanism (Sullivan, 2000; Wang, Chiang, & Lin, 2009). Knowledge markets can enhance knowledge management practices within an organization, and knowledge markets form when companies realize the inadequacy of their own knowledge and begin to search for external knowledge. In a knowledge market, a transaction can take various forms, including human resources, technologies, and patents (Chesbrough, 2003; Davenport & Prusak, 1998; Kevin & Yukika, 2003).

Most knowledge markets lack adequately reliable information that can identify knowledge sources, explaining why businesses must identify for such sources by themselves in a process that consumes much time and energy. Although capable of identifying an appropriate knowledge supplier, both parties might still hesitate to engage in such transactions due to a lack of trust and understanding. A discrepancy thus arises in their respective perceptions of knowledge value and the uncertainty in the ultimate rewards for knowledge. Specifically, knowledge valuation encompasses a diverse array of objective and subjective factors for both the buyer and the seller and lacks uniform pricing standards. Moreover, the absence of a clear pricing structure in the knowledge market contributes to the ambiguity in incentives for knowledge sharing. Consequently, knowledge requesters often relinquish optimal knowledge and settle for substitutive knowledge offered by other suppliers who are more accessible or familiar to them.

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With the burgeoning growth of e-Commerce (Cao & Chai, 2004) and the Internet, online transactions offer buyers and sellers more choices while saving tremendous amounts of time and cost for transactions (Laudon & Traver, 2003; Turban, King, Viehland, & Lee, 2008). Skyrme (2001) proposed an online knowledge transaction model, i.e. knowledge business, that integrates knowledge management and e-Commerce. Although websites with various modes of transactions and exchanges focus on trading business knowledge and intellectual properties, e.g., Knowledgeshop.com, InfoMarkets.com, and www.pl-x.com, a serious obstacle remains in knowledge commerce (k-commerce) where knowledge is sold as a product: in addition, no methods are available to assess the reliability and value of knowledge, as well as its source. In an electronic market for physical products, buyers can access complete product information, including detailed product specifications, product photographs from varying angles, and appraisal reviewers by buyers (Wang & Lin, 2008). In k-commerce, however, buyers cannot peruse complete product information and must rely on a limited description of product specifications and a fragmented knowledge summary to make purchasing decisions. Buyers have full control over how much information of a knowledge product is disclosed. Request specifications for knowledge often vary among knowledge requesters. Excessively disclosing knowledge contents might result in providing the knowledge for free to the requester, while disclosing an insufficient amount may jeopardize the transaction by discouraging the requester. For the buyer, an inadequate understanding of supply and demand in a knowledge market may lead to inappropriate pricing, subsequently incurring market failure and loss of interests for both the buyer and the seller. Consequently, a relatively objective method for automated knowledge valuation must be developed as a valuable reference for both parties and to ensure a functioning knowledge market.

Knowledge valuation-related issues include the following: unclear valuation indicators; unstructured and inconsistent content of knowledge, complicating the ability to infer the potential value of new knowledge products from transaction records of similar products based on the nature of knowledge; inaccessibility to specific background information of product R&D, e.g., processes and costs; and risks in use value: since digesting and adapting knowledge after it has been purchased takes a considerable amount of time, the original knowledge value diminishes if a substitutive product appears before the knowledge value has been realized, not to mention its inability to be fully realized.

This study develops a feasible valuation method for knowledge products in a k-commerce environment. The proposed method can estimate the market value of a product based on knowledge inventor capability, reputation of the knowledge supplier, innovative degree of knowledge, and records of similar product transactions, to support more rational and accurate decision-making for the seller's pricing or selection of the buyer's product, thereby encouraging market transactions by mitigating information asymmetry and risks while increasing transparency during a transaction. Specifically, this study has the following tasks: identify knowledge valuation indicators in k-commerce, design a knowledge valuation factor model, develop a knowledge value ontology (KVO), and develop a multi-aspect knowledge valuation method based on these knowledge valuation indicators.

2. Literature review

This section attempts to identify the importance of this study and analyze k-commerce by exploring three relevant topics: k-commerce, intellectual assets and valuation of technological knowledge.

2.1. k-Commerce

Knowledge business models attempt to use organizational knowledge in order to transmit knowledge from creators to consumers by adopting powerful marketing and transmission tools (Kafentzis, Mentzas, Apostolou, & Georgolios, 2004). Knowledge commerce a series of planned business processes that generates profits through trading and exchanging knowledge online, forming virtual teams for offering unique knowledge services to knowledge requesters, and refining existing knowledge or combining different knowledge to devise new knowledge (Chen & Chen, 2009). When enterprise knowledge is transferred to other enterprises, various factors, e.g., mindsets, languages and ontological concepts, may contribute to knowledge heterogeneity among knowledge users or within the system, thus creating the demand for the following competences: evaluating knowledge content, potential users and knowledge value; providing consistent access to knowledge under a distributed mode; and seamlessly integrating heterogeneous knowledge stored in various depositories (Kafentzis et al., 2004).

Skyrme (2001) asserted that a comprehensive k-commerce architecture must enable the following services:

(1) Knowledge assets: the initial step towards selling knowledge products is to analyze what knowledge assets can be commercialized, if market demand is available for certain product types and the seller's strengths before developing the products/services portfolio and marketing and distribution strategies;
(2) Products and services: depending on user requirements, knowledge must occasionally be integrated with other knowledge in the knowledge supply chain to form new, sellable knowledge;
(3) Marketing and delivery: knowledge is non-physical and thus requires special modes of packaging and marketing. Delivery modes and payment for knowledge products are more complex than physical ones since knowledge requests often depend on contextual factors like specific issues concerned as well as the time and space that the requester is in; and
(4) Customer experience: this service focuses on defining the target customer segment, understanding their needs and offering value-added services.

2.2. Intellectual assets

Intellectual assets (IAs) are increasingly important in both the knowledge economy and corporate asset valuation, which is especially true for knowledge-based enterprises (Harrison, 2007; Sumi, 2008). The Internet provides enterprises with an IA market that offers unprecedented opportunities by enabling rapid and large-volume production, utilization, replication, sale, and exchange of IAs, yet that simultaneously enables infringement behaviors such as counterfeiting or plagiarizing of IAs. Knowledge commerce includes the sale and licensing of IAs, as well as the digitization of intellectual works for expediency, which has created numerous problems. Intellectual property rights (IPR) (Hlupic & Qureshi, 2003; Harrison, 2007) in k-commerce denote various tangible and intangible innovations, including copyrights, patents, trademarks, and field names.

The conventional approach to managing IAs, as currently adopted by most industries, maintains that patents, copyrights, and trademarks should be utilized to adequately control and protect innovative resources unique to an enterprise (Hlupic & Qureshi, 2003). Characterized by their easy sharing, mixing, and reuse for various purposes, digital creations are also readily replicable. From the perspective of the conventional management approach to IAs, digitization has undoubtedly created unprecedented infringement problems for digital authors. Some smart enterprises have adopted a balanced approach to managing their IAs by protecting certain assets while sharing others, thus enabling them to usher in new products that win market.

Skyrme (2001) noted that in knowledge commercialization, products and services may vary with objects and individuals, which may be closely related to the structural capital and human capital of an organization. Product-related factors that are crucial to successful product commercialization include brand image, customer relations, knowledge presentation mode, supplier's reputation and level of services, all of which contribute to product appeal to the buyer and the user. Knowledge products and services are either people-based or object-based. The former is more flexible since the product contents can be adjusted to the context and their monetary rewards are higher; however, the latter can be easily replicated and resold due to their higher degrees of explicitness.

2.3. Knowledge valuation

Technological knowledge can be valued in two ways: (1) a requirement assessment that determines whether a certain technology is worth investing (buying) or commercializing (selling), and (2) an impact assessment of the technology on the economy and society as a whole. The former requires information of the developer's business operations and background, while the latter relies on long-term observation and recordation of the technology as well as an extensive and accurate collection of data. In the knowledge supply chain, knowledge service suppliers play a third-party, mediatory role that requires knowledge valuation from a holistic, fair and objective perspective in order to quickly satisfy the requirements of both buyer and seller, while enabling expedience and multiple choices. Consequently, knowledge valuation from the perspective of knowledge service providers facilitates smooth transactions by offering both parties a set of guidelines that resemble the display function for physical products. Regardless of the perspective adopted, evaluation can be qualitative, quantitative or a mixture of both. Qualitative methods rely on professional knowledge from field experts; quantitative methods involve evaluation formulae based on accumulated data; and the mixed methods combine the two approaches. Major quantitative methods include the following:

(1) Cost methods: the costs of input are the basis for valuation, and such costs include R&D costs, learning costs, and opportunity costs. In k-commerce, accurate labor costs for the producer are unavailable, and personal background and characteristics vary with individuals. Consequently, output quality is not positively related to labor costs, implying that higher costs do not always lead to better output quality;
(2) Benefit methods: valuation is performed based on benefits generated for the user after use. Since benefits of the same knowledge product may vary with requesters and the buyer incurs such benefits only after a certain period of knowledge digestion. These methods are infeasible for pre-transaction valuation;
(3) Market methods: the technology to be valuated and similar products in the recent period are compared if such comparable products are available; and
(4) Bidding methods: product value is determined by the market through bidding or auction, which may be inappropriate in k-commerce where the product value is determined only after the transaction has been made. Whereas valuation function is mainly to serve as a reference for both parties before the deal.

Valuation indicators lack preset standards and may vary with perspectives (macro versus micro), roles (demand and supply sides of the technology, technology investor and broker as the third party), industry of the technology concerned and valuation methods. The focus of technology valuation may change at various stages of the technology lifecycle (Foster, 1986). During the initial invention stage, valuation generally focuses on originating and evaluating ideas. Additionally, the risk is relatively low since it does not involve enormous developmental costs. The maturity stage focuses on whether the technology concerned can become a mainstream technology. Moreover, during the recession stage, valuation centers around the potential of alternative technologies and the residual value of existing technologies.

Above discussions on technological knowledge valuation indicators have revealed that some valuation indicators can be rather abstract, such as functions and breadth of the technology, practical value of the technology, product liability, scope of authorization as well as those indicators for external factors. Such indicators can only be left to expert to judgment, giving rise to the issue of subjectivity. Furthermore, as mentioned earlier in this section, valuation indicators to be adopted also vary with the appraiser's roles, requirements, and the industries of the technology concerned. For instance, the Advanced Technology Program (ATP) in the United States uses the following valuation indicators for key technologies and knowledge: knowledge density per technology classification unit, key technologies, basic technologies, functions and breadth (scope) of the technology, precedent technologies, outstanding issues involving the technology, practical value of the technology, number of patents, number of patent citations, indicator for the quality and quantity of patent portfolio, technological strength, technological cycle, scientific linkage, and scientific strength (Abernathy & Utterback, 1978; MaGee, 1977; Wang et al., 2009).

3. Design of knowledge valuation factor model

Based on a literature review and preliminary analysis of knowledge valuation factors in the above section, this section analyzes knowledge valuation activities and valuation factors to propose an effective knowledge valuation factor model. A KVO is also developed when formulating a knowledge valuation method to serve as the basis for comparison with similar products.

3.1. Scenario for knowledge valuation activities in k-commerce

Selling a knowledge product for business profit initially involves that the knowledge supplier uploads the product along with a description of its features and contents to inform the knowledge requestor of the name, type, keywords, background introduction, applications and potential benefits of the knowledge product. Once created by the supplier, the knowledge product description, which is semi-structured, must be converted into product presentation with a unified format so as to avoid diluting the knowledge value by disclosing the full knowledge contents. In this study, such presentations are stored in the knowledge product depository in the form of knowledge product ontology model. A knowledge product ontology model adopts the notion of ontology (Lee, Jian, & Huang, 2005; Yuan & Sun, 2005) to extract concept knowledge (CK) from knowledge descriptions and contents and, then, associate these CKs with various relationships. Thereafter, the k-commerce platform should be able to retrieve key concepts of a knowledge product to create a conceptual structure that acts as the data source for subsequent processes of product classification, valuation and search. Finally, knowledge valuation is performed at the platform, and the outcome is stored in the knowledge product depository.

When searching for knowledge products, the knowledge requestor can access knowledge product descriptions as well as results of knowledge valuation that serve as a valuable reference for rational decision making in purchasing knowledge. To enhance the fairness and reference value of knowledge valuation, the platform can offer expert knowledge valuation services. Based on the expert data stored in the expert depository, the platform conducts matching by analyzing the competences and expertise of field experts to identify multiple adequate appraisers in the related field and request their assistance in knowledge valuation. Upon the completion of knowledge valuation by experts, the results are returned and stored in the knowledge product depository to serve as a valuable reference for requestors. In return, knowledge valuation experts receive new knowledge and a service fee for their knowledge valuation service.

3.2. Knowledge valuation factor model

Based on the literature review in Section 2.3, quantitative methods for technological knowledge valuation were compiled to analyze their feasible valuation factors. Owing to the constraint of limited knowledge information available in k-commerce, this study identified the following five evaluation aspects containing seven major evaluation factors to develop a knowledge valuation factor model (Fig. 1):

(1) Knowledge inventor capability: Knowledge is embedded with experiences and skills of the inventor. Consequently, knowledge product quality is closely related to the experiences and capabilities of individual inventors. Since the R&D capabilities of the inventor are implicit and cannot be materialized or classified, the quality and quantity of published scientific papers and patents acquired by the inventor are used as the valuation indicator for R&D capabilities in this study;
(2) Knowledge supplier reputation: Teece (1992), Auster (1990) and Howarth (1994) conferred that a supplier's reputation directly impacts the buyer's willingness to purchase knowledge. For the buyer, a low supplier reputation implies a high risk and ultimately a low exchange value of the product. Yamamoto and Ohta (2001), and Bidault and Fischer (1994) asserted that evaluating customer satisfaction and the reputation of the knowledge supplier motivate the knowledge supplier to provide better knowledge products and stimulate the buyer's willingness to purchase. Therefore, this study evaluates the supplier's reputation according to the buyer's opinions. The supplier's reputation is thus used as the main factor for knowledge valuation. This study evaluates the knowledge provider based on post-transaction opinions based on the following six aspects: (1) brand, i.e. evaluating the knowledge brand or company of the supplier; (2) knowledge validity, i.e. evaluating the correctness of a knowledge product after reading, learning and using such knowledge; (3) knowledge explicitness, i.e. evaluating the explicitness of descriptions of content or methodology of the purchased knowledge; (4) knowledge coincidence, i.e. evaluating the extent to which the actual knowledge thus purchased matches the knowledge product descriptions the buyer has read before the purchase; (5) price rationality (PR), i.e. evaluating the rationality of cost against the knowledge thus acquired; and (6) after-sales service (ASS), i.e. rating after-sales services;
(3) Knowledge innovative degree: In an ontology-based approach to knowledge presentation, knowledge is path-dependent and its life cycle is closely related to technology innovativeness. Therefore, this study adopts qualitative and quantitative approaches to evaluating knowledge innovativeness. Path-dependence refers to the degree of similarity between new and existing knowledge. Knowledge that is highly path-dependent belongs to competence enhancing innovations, or innovations derived from existing knowledge. On the other hand, knowledge that is lowly path-dependent or even overruling existing knowledge belongs to competence destroying innovations, which have a higher degree of innovativeness than those of competence enhancing innovations. Furthermore, the current status of knowledge development can be reflected in the knowledge life cycle, which provides a quantitative perspective to observing knowledge innovativeness by the number of individuals involved in studying this knowledge. Knowledge development can be divided into three stages: initial invention, maturity and recession stages (Foster, 1986). In the initial invention stage, the technology concerned is still under a chaotic state as its developmental direction remains unclear. High risks are involved in technological applications and the market is very uncertain, leading to a high uncertainty of the knowledge value;

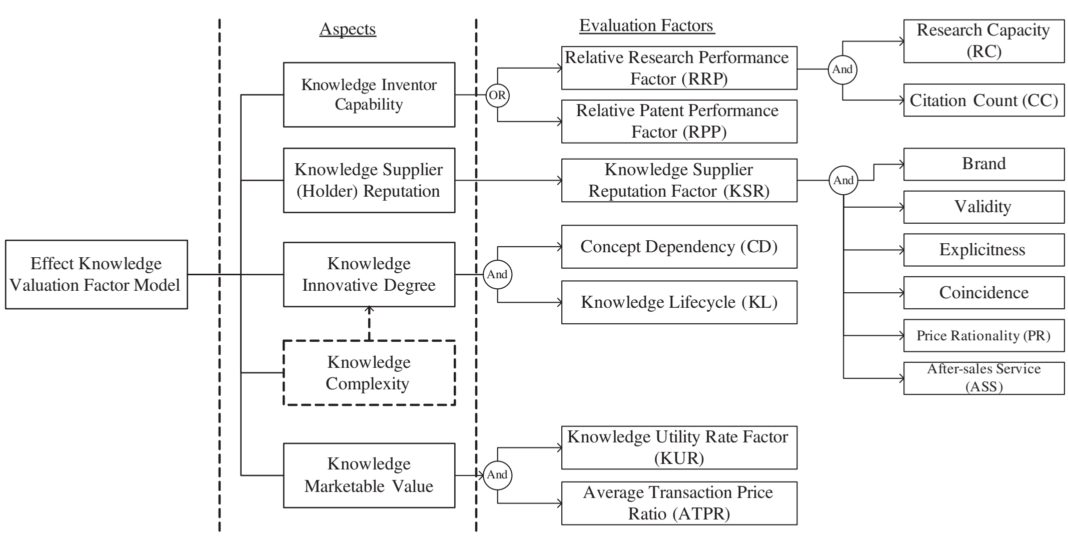

Fig. 1. Knowledge valuation factor model in k-commerce.

(4) Knowledge complexity: With respect to the developer, a larger number of domains that the knowledge concerned covers imply a greater likelihood that an interdisciplinary team is required for its R&D. Hence, a greater heterogeneity implies more time and manpower that are required for R&D. A high degree of heterogeneity requires broad knowledge based on the knowledge requestor to comprehend the knowledge content, leading to a high complexity (Tyre, 1991). This study attempts to determine knowledge complexity by knowledge breadth, features and CK number to support an evaluation of the innovative degree of knowledge; and
(5) Knowledge marketable value: The uniqueness of a knowledge product leads to the unavailability of transaction records of the corresponding knowledge that serve as a knowledge product value reference. Therefore, this study designs a KVO that consists of CKs, relationships between CKs and transaction records of the knowledge market to reflect the history of traded knowledge values and the market demand. In this KVO, each CK can be included in multiple knowledge contents. This frequency relationship of each CK can be used to define the importance or necessity of that CK. A higher number of knowledge contents containing a CK imply a stronger importance or necessity of that CK. A CK with a high importance does not guarantee a high market value since it may only be a required CK for the knowledge concerned. Some CKs that are relatively novel may not have been often included in knowledge, despite the fact that they may be the major concepts contributing to the knowledge. This aspect includes matching CKs of the knowledge with KCs of the KVO, thus reflecting the dynamic market value of knowledge based on the average trading volume of CKs.

3.3. Knowledge value ontology

To assess the innovativeness, complexity and market value of a knowledge product, this section introduces a novel ontology-based KVO to describe how dependence and evolution between CKs are related, and to record CK transaction processes. The proposed KVO is gradually constructed with transaction data, which is constantly maintained and adjusted to accurately reflect changes in the knowledge market in real time. The marketability and significance of the knowledge can be analyzed to determine the value of a newly-launched knowledge product by matching CKs with a known value and those with an unknown value in a knowledge product for valuation in a KVO.

Ontology consists mainly of concept class, properties, instance and relation (Lee et al., 2005; Yuan & Sun, 2005). The generic KVO model (the left of Fig. 2) comprises concept knowledge class and three relationships. The three relationships, i.e. *generalization*, *aggregation* and *association*, were originally defined in object-oriented ontology. To construct the KVO, the three relationships have been redefined. *Generalization relationship* refers to the relationship "is a" between two CKs, *aggregation relationship* represents the relationship "part of" between two CKs, and *association relationship* can be further defined into different relationships by an administrator, e.g., "sequential relationship" expresses the sequence between two CKs and "evolutional relationship" expresses the evolutional status between CKs. Table 1 lists the definitions of the properties in CK class.

The right portion of Fig. 2 illustrates an example of KVO, including three CKs, i.e. Trust Evaluation Method (CK221), social network-based Trust Evaluation Method (CK225) and social network (CK300), in which CK225 evolves from CK221, and CK300 is a part of CK225.

Based on the knowledge valuation factor model and KVO proposed in this section, four knowledge valuation sub-methods included in the multi-aspect method are developed in Sections 4–7, respectively.

4. Knowledge inventor capability evaluation

Based on valuation factors of the first aspect, this section introduces a novel knowledge inventor capability evaluation method. The proposed method features a quantitative approach to assess the knowledge inventor capability according to the two indicators (relative research performance (RRP) and relative patent performance (RPP)) to serve as an indirect reference for determining the quality of knowledge. Academia usually values the scientific publications in international journals, whereas industry tends to more heavily emphasize patent performance. Importantly, the proposed method can choose either or both indicators for valuation based on the background of the knowledge inventor.

4.1. Performance evaluation of relative research

Performance evaluation of relative research mainly considers two indicators: research capacity (RC) and citation count (CC).

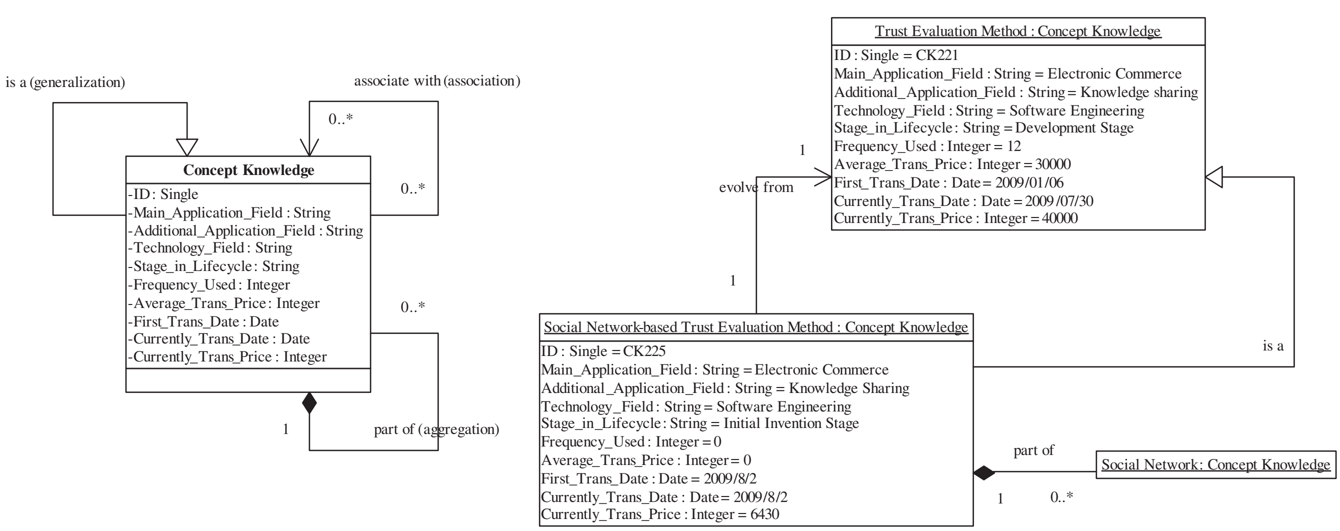

Fig. 2. Knowledge value ontology.

Table 1
Definitions of the properties in CK class.

Property	Description
Identification (ID)	Indicates the unique identification of the CK object
Main_Application_Field	Indicates the CK object can mainly be applied to which field or industry
Additional_Application_Field	Indicates the CK object can be applied to which additional field or industry
Technology_Field	Indicates the CK object belongs to what technology field, for example RFID
Stage_in_Lifecycle	Indicates the CK object belongs to one of three stages of lifecycle, including initial invention, development and maturity stages
Frequency_Used	Indicates the frequency of the CK object applied
Average_Trans_Price	Indicates the average price of all historical transactions
First_Trans_Date	Indicates the date that the CK object is transacted first
Currently_Trans_Date	Indicates the date that the CK object is transacted currently
Currently_Trans_Price	Indicates the price that the CK object is transacted currently

Table 2
Degree of author contribution ($w_j(k)$).

Author	Number of authors				
	1 Author	2 Authors	3 Authors	4 Authors	⩾5 Authors
First author	1/1	2/3	3/6	4/10	4/10
Second author	None	1/3	2/6	3/10	3/10
Third author	None	None	1/6	2/10	2/10
Fourth author	None	None	None	1/10	1/10
Fifth author and ...	None	None	None	None	0/10

Research capacity measures the quality and quantity of the researcher's output capacity by considering the number of publications in academic journals, impact factor (IF) of the journals and number and order of authors. The author' contribution to a published paper decreases with an increasing number of authors and a decreasing order of the author in a publication.

Specific distributions of patents and published papers by researchers vary with industries and fields, explaining why the performance of individual researchers becomes meaningless unless it is compared with other researchers in the same field. The method that evaluates the performance of relative research ranks the author's contribution in a descending order of arithmetic progression based on the number of authors and the order of the researcher in each published paper. Based on these principles, the degree of author contribution (Table 2) was devised to determine the contribution $w_j(k)$ by researcher (k) in a published paper (j). This contribution degree can be made more flexible in the future when the requestor can assign specific values. If the number of authors in a paper exceeds 4, then the contribution of an author ranking 4th and afterwards in the order is 0. For instance, consider a paper with three authors. The contribution degree is 1/2 for the first author, 1/3 for the second author, and 1/6 for the third author, all of which are entered in Function (1) to calculate the research capacity of the developer.

$$RC(f,r) = \sum_{j=1}^{m} IF_{fj} \times w_j(r), \tag{1}$$

where $RC(f,r)$ denotes the research capability of inventor r on field f; IF_{fj} denotes the impact factor of the jth journal paper on f written by r, $1 \leqslant j \leqslant m$; m denotes the number of papers written by r; and $w_j(k)$ represents the contribution degree of r on his/her jth paper.

Since the importance of a research is often based on the number of citations, this method incorporates the number count to make adjustments to the research performance. Using Function (2) calculates the relative citation value of the inventor ($C(f,r)$), which considers the number of citations for the individual as well as the relative value against other inventors in the same field.

$$C(f,r) = \begin{cases} \frac{CI_f(r) - CI_f^{\min}}{CI_f^{\max} - CI_f^{\min}} & \text{if} \quad CI_f(r) \geqslant CI_f^{\min} \\ 0 & \text{if} \quad CI_f(r) = CI_f^{\min} \end{cases}, \tag{2}$$

where $C(f,r)$ represents the relative citation value of inventor r on field f; $CI_f(r)$ represents the total count of papers written by r on field f and cited by other papers; and $CI_f^{\min}$ and $CI_f^{\max}$ represent the total minimum and maximum citation counts of papers of other inventors on field f.

Finally, the relative research performance of inventor r on field f ($RRP(f,r)$) is calculated using Function (3). The relative research performance is greater than or equal to "0." The relative research performance improves with a high value of the performance.

$$RRP(f,r) = RC(f,r) + C(f,r), \tag{3}$$

where $RC(f,r)$ represents the research capability of r on field f; and $C(f,r)$ represents the relative citation value of r on field f.

4.2. Performance evaluation of relative patents

Industries increasingly value patents and their protection, often regarding patents as an indicator for competitiveness (Podolny, Stuart, & Hannan, 1996). A patent frequently cited by other patents implies that it owns greater value than less frequently cited patents. Indicators related to patent citation include science technology links, current impact indices, total incoming citation counts, and incremental differences in citation count (Wang et al., 2009). Consequently, this aspect also includes the number of patents by researchers in the same field and their patent citation counts to determine the value and quality of the patent concerned. Function (4) describes this process, in which the relative patent performance ($RPP(f,r)$) of the inventor (r) in field (f) is determined. Since many patents lack a value derived from actual applications, patent citation count should become an important indicator for inventor patent performance. Therefore, Function (4) attaches an equivalent weight to patent count and patent citation count. As shown in Function (4), the relative patent performance of each inventor falls within the range of [0,2]: a value closer to 2 implies a higher research performance of the inventor.

$$RPP(f,r)=\begin{cases}\frac{P_f(r)-P_f^{\min}}{P_f^{\max}-P_d^{\min}}+\frac{PC_f(r)-PC_f^{\min}}{PC_f^{\max}-PC_f^{\min}} & \text{if} \quad P_f(r)\neq P_f^{\min}\wedge PC_f(r)\neq PC_f^{\min}\\ \frac{P_f(r)-P_f^{\min}}{P_f^{\max}-P_f^{\min}} & \text{if} \quad PC_f(r)=PC_f^{\min}\\ \frac{PC_f(r)-PC_f^{\min}}{PC_f^{\max}-PC_f^{\min}} & \text{if} \quad P_f(r)=P_f^{\min}\\ 0 & \text{if} \quad P_f(r)=P_f^{\min}\wedge PC_f(r)=PC_f^{\min},\end{cases} \tag{4}$$

where $P_f(r)$ denotes the number of patents developed by inventor r in field f; $P_f^{\max}$ and $P_f^{\min}$ denote the maximum and minimum of patents developed by other single inventors, respectively; $PC_f(r)$ represents the total count of all patents developed by r and cited by other patents or scientific papers; and $PC_f^{\max}$ and$PC_f^{\min}$ represent the total maximum and minimum citation counts of patents developed by other single inventors, respectively.

4.3. Example of applying the knowledge inventor capability evaluation sub-method

To introduce the sub-method and the following other sub-methods, this study considered an example in which a knowledge product named "social network-based Trust Evaluation Method for knowledge sharing among collaborators" is submitted to a k-commerce platform by its inventor surnamed Chen. The platform must evaluate the quality and value of the knowledge for knowledge seekers and requesters. Therefore, relative research and patent performances of Chen are evaluated below.

4.3.1. Performance evaluation of relative research

The list of papers and authors related to the inventor Chen shown in Table 3 includes three papers written by Chen. Profiles of the inventors are stored in a customer database of the k-commerce platform. The three papers had been published in different journals that belong to a research field called resource sharing (RS). To evaluate Chen's relative research performance, Function (1) is used and the degree of author contribution listed in Table 2 is applied to derive

$$RC(\text{RS},\text{Chen})=2.014\times\frac{3}{10}+0.722\times\frac{4}{10}+2.596\times\frac{2}{3}=2.6237.$$

Table 3
List of papers and authors.

The sequence of the evaluated author/number of all authors	Paper title	Journal	Impact factor	Citation count
2/4	Design of a meta model for enterprise system integration	Computers in industry	2.014	12
1/4	Distributed access control architecture and model for supporting collaboration and concurrency in dynamic virtual enterprise	International journal of computer integrated manufacturing	0.722	8
1/2	Advanced multi-phase trust evaluation model for collaboration between coworkers in dynamic virtual project teams	Expert system with applications	2.596	3

In the above example, assume that $CI_{f=\text{RS}}^{\min}$ and $CI_{f=\text{RS}}^{\max}$ are 5 and 50, respectively, and apply them to Function (2), resulting in

$$C(\text{RS},\text{Chen})=\frac{(12+8+3)-5}{50-5}=0.4.$$

Substituting the results of Functions (1) and (2) into Function (3) yields

$$RRP(\text{RS},\text{Chen})=2.6237+0.4=3.0237.$$

Finally the relative research performance of inventor Chen is 3.0237.

4.3.2. Performance evaluation of relative patents

A situation was examined in which the inventor Chen has 6 patents in the RS research field, which had been quoted by other companies 20 frequencies. Results of the performance evaluation of relative patents are compared by assuming that another inventor surnamed Yang has 25 patents, which had been quoted by other companies 78 frequencies. In the RS field, the maximum and minimum numbers of patents are 2 and 27, respectively; in addition, the maximum and minimum numbers of citation counts of patents are 0 and 100, respectively. Incorporating the above data into Function (4), the result is

$$RPP(\text{RS},\text{Chen})=\frac{6-2}{27-2}+\frac{20-0}{100-0}=0.36,\quad\text{and}$$
$$RPP(\text{RS},\text{Yang})=\frac{25-2}{27-2}+\frac{78-0}{100-0}=1.7.$$

The relative patent performances of inventors Chen and Yang related to RS are 0.36 and 1.7, respectively. Hence, the relative patent performance of Yang is better than that of Chen's. In a k-commerce platform, the relative research and patent performances of other inventors in the RS field can rapidly be computed using the two sub-methods. The relative research and patent performances of the evaluated inventor can be compared with other inventors to assess the quality of knowledge invented by the evaluated inventor.

5. Evaluation of a knowledge supplier's reputation

Evaluation of online transactions is a valuable reference for purchase decisions. However, concerns over anonymity and a lax security validation procedure in online trading have resulted in fake or forged evaluations, ultimately leading to a low reference value of such evaluations (Wang & Chiu, 2008; Rathnam, 2005). In the supplier reputation aspect of knowledge valuation, this study develops a fuzzy-based inference method to evaluate the reputation of knowledge suppliers by incorporating social network analysis. Upon the completion of knowledge trading, based on user experience, the buyer can evaluate the six appraisal factors proposed in the knowledge valuation factor model. The six appraisal factors include Brand, Validity, Explicitness, Coincidence, price rationality (PR) and after-sales service (ASS), whose values are divided into five ranks: "excellent," "good," "fair," "poor," and "bad." Each rank is assigned a score in the order of 5, 4, 3, 2, and 1.

The proposed fuzzy-based supplier reputation inference sub-method (Fig. 3) consists of three phases, i.e. deleting exceptional appraisal, clustering, and reputation fuzzy inference phases, whose activities are described in detail in the following subsections.

5.1. Deleting the exceptional appraisals (Phase 1)

Based on a social network of Wang, Chiu, and Ker (2005) for analyzing transaction evaluators, this phase detects and deletes potential abnormal appraisers in appraisal records to ensure

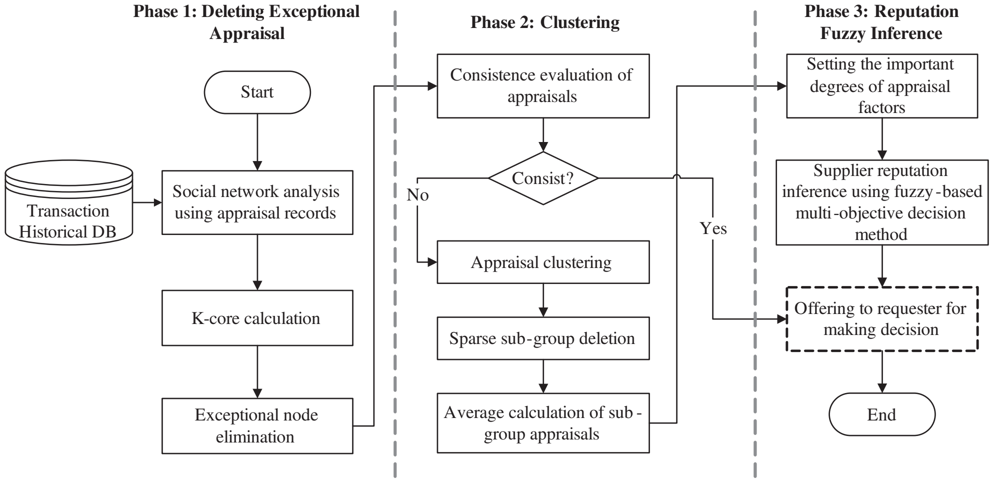

Fig. 3. Fuzzy-based supplier reputation inference process.

fairness in valuation. This phase includes the following three processes:

5.1.1. Social network analysis

Based on transaction evaluation records of the appraisee (knowledge supplier), first the first-layer transaction network relation matrix (Table 4) for the appraisee and the appraiser (the buyer) is generated. According to Table 4, column 1 represents the appraisee, and row 1 the appraiser. Grid value "1" refers to a situation in which transactions occur between both parties and "0" represents no transactions. To introduce the method, this sub-method uses the same example in Section 4.3. Table 4 lists the transaction data, in which r1, r2, r3, r4, r5, r6 and r12 had transactions with supplier Chen (s1). Also, this table can be used to construct the first-layer transaction social network (the left of Fig. 4), where the arrow represents the process flow of knowledge product.

Next, based on the first-layer transaction social network, those having transactions with r1, r2, r3, r4, r5, r6 and r12 were identified. The first-layer transaction network relation matrix was then expanded into the second-layer transaction network relation matrix (Table 5), on the basis of which the second-layer transaction social network can be constructed, as shown in the right portion of Fig. 4.

5.1.2. Calculating k-core

k-Core is an important indicator for measuring a sub-group and represents the maximal sub-group of all notes that have at least k relations with other network nodes.

According to Wang et al. (2005), normal online transactions have a 1-core network structure. Therefore, exceptional transactions can be detected in a 2-core network structure. In this process, k-core was estimated using the k-core algorithm for the second-layer transaction network, as proposed by Batagelj and Zaversnik (2003). By using the right portion of Fig. 4 as an example, nodes r1, r2, r3, r4, r5, r8 and r9 meet 1-core sub-group, and the nodes r5, r6, r7 and r12 meet 2-core sub-group. Understanding the social network structure allows one to identify the exceptional relationships among nodes.

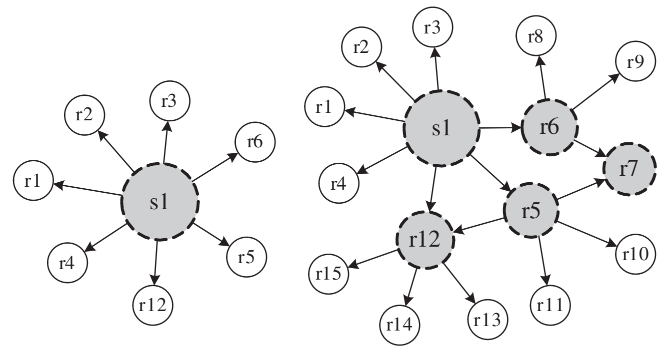

Fig. 4. The first and second transaction social networks.

5.1.3. Deleting exceptional nodes

Nodes that are 2-core and have transaction records with inventor Chen are deleted. In the right portion of Fig. 4, nodes r5, r6 and r12 were 2-core sub-groups and had transactions with Chen. Consequently, appraisal records of Chen at these nodes were screened to sanitize subsequent calculations of supplier reputation value by diminishing the interference of exceptional appraisals.

5.2. Appraisal clustering (Phase 2)

After exceptional appraisals have been deleted in Phase 1, the remaining appraisals may encompass a wide variety of positive

Table 4
The first-layer relation matrix.

Sellers	Buyers														
	Chen (s1)	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15
Chen (s1)		1	1	1	1	1	1	0	0	0	0	0	1	0	0	0
r2	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0
r3	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0
...																

Table 5
The second-layer relation matrix.

Sellers	Buyers														
	Chen (s1)	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15
Chen (s1)	–	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0
r1	0	–	0	0	0	0	0	0	0	0	0	0	0	0	0	0
r2	0	0	–	0	0	0	0	0	0	0	0	0	0	0	0	0
r3	0	0	0	–	0	0	0	0	0	0	0	0	0	0	0	0
r4	0	0	0	0	–	0	0	0	0	0	0	0	0	0	0	0
r5	0	0	0	0	0	–	0	1	0	0	1	1	1	0	0	0
r6	0	0	0	0	0	0	–	1	1	1	0	0	0	0	0	0
...																

and negative ones. Clustering is then performed in this phase. Clustering methods are adopted when no class or group is predicated, but rather when the instances are to be divided into natural groups (Hartigan, 1975; Harmerly & Elkan, 2002; Jain, Murty, & Flynn, 1999; Witten & Frank, 2000; Wu, Liu, & Luo, 2008). This phase comprises three processes:

5.2.1. Consistency evaluation of appraisals
The consistency in appraisals is analyzed based on the valuation by each appraiser to determine whether appraisers have found a consistent appraisal of the knowledge. For instance, if only extremely few appraisals have negative opinions and the rest are all positive, then the appraisal conclusion can be provided directly to the requestor as a reference.

5.2.2. Appraisal clustering
If appraisal opinions significantly diverge, clustering algorithm is then used to cluster appraisals according to values of valuation indicators of each appraisal.

5.2.3. Deleting sparse sub-groups
This process eliminates opinions of minority dissidents by deleting spare sub-groups.

5.2.4. Calculating the average of appraisals
The average of each valuation indicator of appraisals in each remaining sub-group is estimated.

5.3. Supplier reputation inference (Phase 3)

After exceptional appraisers had been deleted during Phase 1, clustering of normal appraisers was performed based on their appraisals during Phase 2. During Phase 3, a reputation fuzzy inference through means of the fuzzy-based multi-objective decision inference method was made to process appraisals on the knowledge supplier in each sub-group in the following two processes:

5.3.1. Setting the importance degree of appraisal factors
The requestor may initially determine the importance degree of an appraisal factor by assigning a weight in the range of [0,1]. For instance, if the requester values most of the knowledge validity, then appraisal factor Validity is set at a value close to "1"; in the opposite case, this value is set close to "0". Let P refer to the importance degree set of appraisal factors for the requestor, then $P = \{p_1, p_2, p_3, p_4, p_5, p_6\}$, in which p_1–p_6 represent appraisal factors of Brand, Validity, Explicitness, Coincidence, PR and ASS, respectively. For instance, $P = \{0.3, 0.9, 0.7, 0.6, 0.8, 0.6\}$ indicates an importance degree of 0.3 for Brand by the requestor.

5.3.2. Supplier reputation inference
In this process, based on P sets of all appraisal factors for the requestor, a subgroup was inferred from multiple sub-groups. This finding implies that the requestor's opinion is consistent with that of the sub-group. Next, the reputation value of the knowledge supplier under evaluation is represented by the opinions of this sub-group. Different weights assigned to appraisal factors lead to different reputation values. Additionally, the set of these sub-groups can be represented by $A = \{a_1, a_2, \ldots, a_n\}$ for n sub-groups. The six indicators for determining supplier reputation are Brand, Validity, Explicitness, Coincidence, PR and ASS, as represented by the set $O = \{o_1, o_2, o_3, o_4, o_5, o_6\}$. Each sub-group contains opinions of multiple buyers on an appraisee. The indicators of these opinions must be averaged and, then, standardized into the range of [0,1]. All six indicators must be considered when the requestor evaluates a knowledge product. Consequently, a fuzzy set $O_i(a_j)$ is utilized to represent cost $O_i$that should be paid when selecting a_j; in addition, the actual decision (D) is represented by Function (5).

$$D(a_i) = \min[o_1(a_i), o_2(a_i), \ldots, o_6(a_i)]. \tag{5}$$

In this study, optimal decisiona^* was inferred using Diense–Rescher Implication (Klir & Yuan, 1995; Zimmermann, 1991), as shown in Function (6).

$$D(a^*) = \max_{a_i \in A} D(a_i) = \max_j[\min_i C_i(a_j)]. \tag{6}$$

5.4. Example of applying the fuzzy-based multi-objective decision inference method

All records containing previous transactions with inventor Chen and related evaluations are identified using the same example in Section 5.1. The six indicators required for decision making are represented by o_1, o_2, o_3, o_4, o_5 and o_6, respectively. Assume that after the processes in Phase 2, all sparse sub-groups have been screened off and three sub-groups remain, as shown in Table 6: Sub-group$_1$, Sub-group$_2$ and Sub-group$_3$, which are represented by a_1, a_2, and a_3, respectively. All indicators of each sub-group are averaged and then standardized into the range of [0,1] (Table 6). Sub-group$_1$ is considered as an example. According to knowledge buyers of this sub-group, their rating for Chen was 0.5 for Brand, 0.8 for Validity, 0.6 for Explicitness, 0.9 for Coincidence, and 0.3 for PR, and 0.4 for ASS. Other sub-groups may have opinions differing from sub-group$_1$. Further compiling these data result in the following situation:

$$\begin{aligned}
&A = \{\text{Sub-group}_1,\ \text{Sub-group}_2,\ \text{Sub-group}_3\} = \{a_1, a_2, a_3\} \\
&O = \{\text{Brand, Validity, Explicitness, Coincidence, PR, ASS}\} \\
&= \{o_1, o_2, o_3, o_4, o_5, o_6\} \\
&P = \{p_1, p_2, p_3, p_4, p_5, p_6\}
\end{aligned}$$

In this study, a fuzzy set $O_i(a_j)$ for A and O was established as follows:

Table 6
List of appraisal factors of candidate sub-groups.

Average of appraisal	Appraisal factor					
Cluster	Brand (o_1)	Validity (o_2)	Explicitness (o_3)	Coincidence (o_4)	PR (o_5)	ASS (o_6)
Sub-group$_1$ (a_1)	0.5	0.8	0.6	0.9	0.3	0.4
Sub-group$_2$ (a_2)	0.8	1.0	0.7	0.6	0.7	0.3
Sub-group$_3$ (a_3)	0.2	0.6	0.8	0.7	0.7	0.9

$$\text{Brand} \Rightarrow O_1 = \frac{0.5}{\text{Sub-group}_1} + \frac{0.8}{\text{Sub-group}_2} + \frac{0.2}{\text{Sub-group}_3}$$

$$\text{Validity} \Rightarrow O_2 = \frac{0.8}{\text{Sub-group}_1} + \frac{1.0}{\text{Sub-group}_2} + \frac{0.6}{\text{Sub-group}_3}$$

$$\text{Explicitness} \Rightarrow O_3 = \frac{0.6}{\text{Sub-group}_1} + \frac{0.7}{\text{Sub-group}_2} + \frac{0.8}{\text{Sub-group}_3}$$

$$\text{Coincidence} \Rightarrow O_4 = \frac{0.9}{\text{Sub-group}_1} + \frac{0.6}{\text{Sub-group}_2} + \frac{0.7}{\text{Sub-group}_3}$$

$$\text{PR} \Rightarrow O_5 = \frac{0.3}{\text{Sub-group}_1} + \frac{0.7}{\text{Sub-group}_2} + \frac{0.7}{\text{Sub-group}_3}$$

$$\text{ASS} \Rightarrow O_6 = \frac{0.4}{\text{Sub-group}_1} + \frac{0.3}{\text{Sub-group}_2} + \frac{0.9}{\text{Sub-group}_3}.$$

Validity indicator is considered as an example for explaining the above inference process. The average validity value for the knowledge in the previous transaction was 0.8 for sub-group$_1$, 1.0 for sub-group$_2$, and 0.6 for sub-group$_3$. Assume that in process 1 of this phase, the weights assigned to different indicators by the requestor were $P = \{0.3, 0.9, 0.7, 0.6, 0.8, 0.6\}$. Then, the appraisal factor of the requestor valued most was Validity ($p_2 = 0.9$) and then PR ($p_5 = 0.8$). Meanwhile, the least important factor was Brand ($p_1 = 0.3$).

$$\begin{aligned}D(a_1) &= D(\text{Sub-group}_1)\\ &= (\bar{p}_1 \vee O_1(a_1)) \wedge (\bar{p}_2 \vee O_2(a_1)) \wedge (\bar{p}_3 \vee O_3(a_1)) \wedge (\bar{p}_4 \vee O_4(a_1))\\ &\quad \wedge (\bar{p}_5 \vee O_5(a_1)) \wedge (\bar{p}_6 \vee O_6(a_1))\\ &= (0.7 \vee 0.5) \wedge (0.1 \vee 0.8) \wedge (0.3 \vee 0.6) \wedge (0.4 \vee 0.9) \wedge (0.2\\ &\quad \vee 0.3) \wedge (0.4 \vee 0.4)\\ &= 0.7 \wedge 0.8 \wedge 0.6 \wedge 0.9 \wedge 0.3 \wedge 0.4 = 0.3.\end{aligned}$$

$$\begin{aligned}D(a_2) &= D(\text{Sub-group}_2)\\ &= (\bar{p}_1 \vee O_1(a_2)) \wedge (\bar{p}_2 \vee O_2(a_2)) \wedge (\bar{p}_3 \vee O_3(a_2)) \wedge (\bar{p}_4 \vee O_4(a_2))\\ &\quad \wedge (\bar{p}_5 \vee O_5(a_2)) \wedge (\bar{p}_6 \vee O_6(a_2))\\ &= (0.7 \vee 0.8) \wedge (0.1 \vee 1.0) \wedge (0.3 \vee 0.7) \wedge (0.4 \vee 0.6) \wedge (0.2\\ &\quad \vee 0.7) \wedge (0.4 \vee 0.3)\\ &= 0.8 \wedge 1.0 \wedge 0.7 \wedge 0.6 \wedge 0.7 \wedge 0.4 = 0.4.\end{aligned}$$

$$\begin{aligned}D(a_3) &= D(\text{Sub-group}_3)\\ &= (\bar{p}_1 \vee O_1(a_3)) \wedge (\bar{p}_2 \vee O_2(a_3)) \wedge (\bar{p}_3 \vee O_3(a_3)) \wedge (\bar{p}_4 \vee O_4(a_3))\\ &\quad \wedge (\bar{p}_5 \vee O_5(a_3)) \wedge (\bar{p}_6 \vee O_6(a_3))\\ &= (0.7 \vee 0.2) \wedge (0.1 \vee 0.6) \wedge (0.3 \vee 0.8) \wedge (0.4 \vee 0.7) \wedge (0.2\\ &\quad \vee 0.7) \wedge (0.4 \vee 0.9)\\ &= 0.7 \wedge 0.6 \wedge 0.8 \wedge 0.7 \wedge 0.7 \wedge 0.9 = 0.6\end{aligned}$$

$$D(a^*) = \max(D(a_1),\ D(a_2),\ D(a_3)) = \max(0.3, 0.4, 0.6) = 0.6.$$

According to the importance of the requestor attached to different indicators of the knowledge product from inventor Chen, the requestor should refer to the reputation appraisal by Sub-group$_3$.

6. Evaluation of innovative degree of knowledge

Based on the two indicators of concept dependency (CD) and knowledge lifecycle (KL), this study develops two evaluation sub-models to evaluate the innovative degree of knowledge, as shown in Sections 6.1 and 6.2.

6.1. Evaluation of concept dependency

Each knowledge product has its own knowledge domain, and multiple CKs can be extracted from its knowledge content to represent knowledge. Such a method determines innovativeness of knowledge concerned by evaluating the similarity between knowledge product and the CKs in KVO. A comparison of concept similarity can be made by methods like the Jaccard Coefficient, which has been adopted for ontology mapping and modified slightly as a similarity calculation based on name, essential information and relationships (Guha, Rastogi, & Shim, 1998; Kong, Hwang, & Kim, 2005). A high degree of similarity between CKs indicates that the knowledge content of a product is developed by expending existing knowledge and has a low degree of innovativeness. This study develops Function (7) to determine concept dependency ($CD(k)$), falling in the range of $[0,1]$, in which a high value indicates high concept dependency and low innovativeness.

$$CD(k) = \frac{|CK(k) \cap CK_{kvo}|}{n} \in [0,1], \tag{7}$$

where $CK(k)$ represents *CKs* included in the evaluated knowledge product k; CK_{kvo} represents *CKs* included in the *KVO*; $|CK(k) \cap CK_{kvo}|$ represents the number of *CKs* that are included in k and the KVO; and n is the number of all *CKs* included in k.

The left portion of Fig. 5 is a part of the KVO. Knowledge K1 is the knowledge product of interest by the requestor, and it was developed by Chen for sale on the k-commerce platform. The right portion of Fig. 5 is the semantic ontology of K1 that has been generated by keyword decomposition and semantic expansion to describe the characteristics of $k1$ in ontological concepts.

Using Fig. 5 as an example, knowledge product K1 includes 4 CKs: K1-CK1, K1-CK2, K1-CK3 and K1-CK4. The similarity is determined using the Jaccard Coefficient. Assume that three of these CKs, i.e. K1-CK1, K1-CK2 and K1-CK3, are similar to the CKs KVO-CK1, KVO-CK4 and KVO-CK3 in the KVO, respectively. Applying all these data to Function (7) yields

$$CD(k1) = \frac{3}{4} = 0.75.$$

Therefore, the concept dependency of knowledge $k1$ is 0.75.

6.2. Evaluation of knowledge lifecycle

Logistic model (Function (8)) features high validity and reliability among S-curve prediction technologies (Ernst (1997)) and, therefore, is adopted in this study as the model for evaluating knowledge lifecycle. A lower resultant lifecycle value implies a lower degree of maturity for knowledge. Evaluating knowledge lifecycle requires the information of the number of organizations currently engaged in related studies on competition. However,

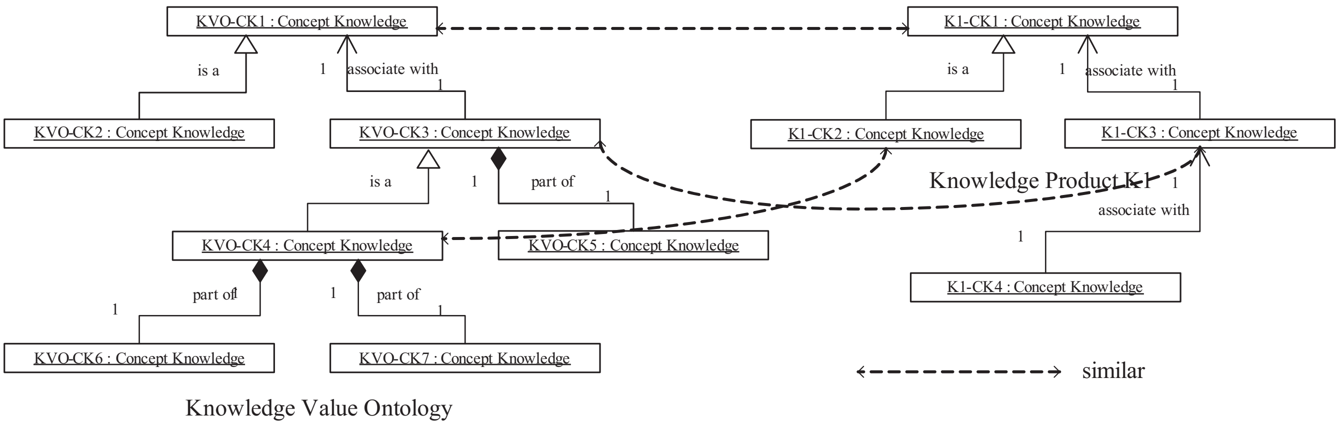

Fig. 5. An example of concept dependency between KP and the KVO.

access to such information is rather difficult due to the constraint of trade secrets. Consequently, knowledge lifecycle can be evaluated only based on the actual circulation of knowledge and number of patents in the knowledge market. In this study, patent count is used as source data for evaluating knowledge lifecycle since patents can accurately reflect the status of technological development in light of the typical characteristics of patents, i.e. relatively early disclosure of technological information and standardized classification.

$$Y(t) = k/1 + e^{-\alpha(\Delta t-\beta)} \in [0,1], \tag{8}$$

where k represents the limit of number of patent increment; α represents growth rate of patent increment; β represents the date of turning point (in months); t represents current time; and $\triangle$t represents the time interval from the earliest (the first patent to be invented) until now.

In the logistic model, the independent variable (x) represents the time interval while the dependent variable (y) represents the accumulated patent count, whose collection is required over time to evaluate the current status of knowledge lifecycle. Using the patents of G06F17/60, G06F17/40 and G06N5/00 in the International Patent Classification (IPC) as examples, this study demonstrates the effectiveness of the approach to evaluating knowledge lifecycle. These IPC classification numbers are used to search for the time duration and accumulated patent count from the patent database WIPO of the International Patent Organization. These patents are listed chronologically (Table 7) and fed into the LogletLab Tool to simulate the logistic curve of knowledge, as shown in Fig. 6. All the times in the simulation results indicate the starting time when the first patent appears (time unit: month), of which x-denotes the time elapsed since the first patent and y-the accumulated patent count. The major item for prediction is the midpoint, i.e. 213.776 months in the case, indicating the maturity stage is reached after 213.776 months. Therefore, whether the knowledge concerned has reached its maturity stage or is still at the initial invention stage can be determined. Knowledge still under development has a higher degree of innovativeness.

7. Evaluation of knowledge marketable value

Evaluating the real value of knowledge can be extremely difficult. For this aspect, the knowledge marketable value evaluation sub-method proposed in this study estimates the values of CKs in knowledge by comparing similarities and corresponding relationships between CKs in knowledge content and the structures of CKs in those knowledge products with transaction records, instead of directly estimating knowledge value. Each CK extracted from a knowledge product can be matched with CKs in the KVO using a similarity comparison method. Referring to the attributes of similar CKs in the KVO, the knowledge requestor can understand approximately the marketable value of knowledge of interest. Based on the three relationships in the KVO, this study proposes

Table 7
List of Patent Data in WIPO.

Year	Classification of patent				
	G06F17/60	G06F17/40	G06N5/00	Subtotal	Accumulative total
1995	2	0	0	2	2
1996	1	0	0	1	3
1997	4	0	0	4	7
1998	1	0	0	1	8
1999	8	0	0	8	16
2000	8	0	0	8	24
2001	29	3	0	32	56
2002	30	1	1	32	88
2003	11	1	0	12	100
2004	27	1	0	28	128
2005	11	4	0	15	143
2006	0	4	15	19	162
2007	2	54	52	108	270
2008	0	102	58	160	430
2009	0	21	12	33	463

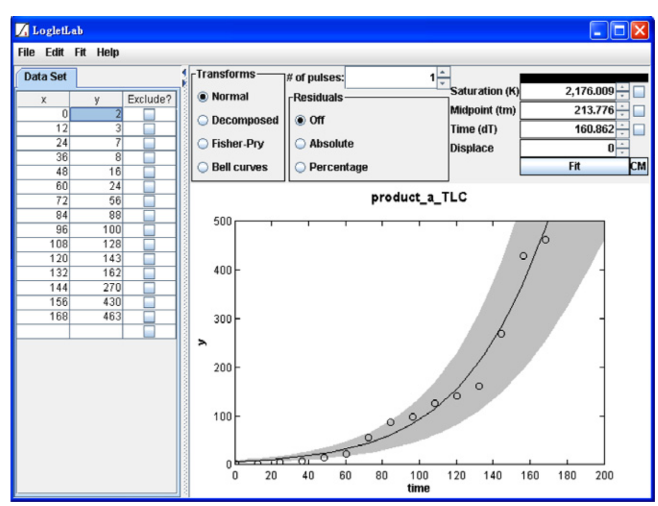

Fig. 6. Knowledge lifecycle evaluation using LogletLab tool.

a valuation principle corresponding to CKs. Consider Fig. 5 as an example:

7.1. Generalization relation model

The "is a" relationship between two CKs refers to a situation in which the two CKs (super-CK and sub-CK in the KVO) are in a main-subordinate relation. In knowledge evolution, the sub-CK is newer than its super-CK. Consequently, the knowledge price range formed by sub-CK and super-CK can serve as a direct reference for the requestor. Consider Fig. 5 as an example. Assume that average transaction prices for KVO-CK1, KVO-CK2, KVO-CK3, KVO-CK4, KVO-CK5, KVO-CK6 and KVO-CK7 are US$100, 120, 80, 90, 20, 30 and 35, respectively. In this example, K1-CK1 is similar to KVO-K1 and KVO-CK2 is a KVO-CK1 because a generalization relation exists between the two CKs. Therefore, requestors can refer to the aver_trans_price attributes of KVO-CK1 and KVO-CK2 to make a decision. The knowledge marketable value via the generation relation function ($MV_g(c_k)$) is shown as Function (9). By applying Function (11) to the example, the value range of the evaluated CK (K1-CK1) is [US$100,US$120].

$$MV_g(c_k) = \begin{cases} [P_{super}, P_{sub}] & \text{if} \quad P_{sub} > P_{super} \\ [P_{sub}, P_{super}] & \text{if} \quad P_{super} \geqslant P_{set}, \end{cases} \tag{9}$$

where two CKs (CK_{super} and CK_{sub}) are included in KVO, CK_{sub} is a sub-class of CK_{super}; c_k is one of the CKs in the evaluated knowledge, and resembles CK_{super} or CK_{sub}; P_{super} andP_{sub} represent the average transaction price of CK_{super} and CK_{sub}, respectively.

7.2. Aggregation relation model

The "part of" relationship between CKs indicates that the two CKs are in a whole-part relationship. Since knowledge is indivisible, the attributes of whole-CK and part-CK may serve as a valuable reference for the requestor. Consider Fig. 5 as an example. Concept knowledge K1-CK2 in knowledge product K1 is similar to concept knowledge KVO-CK4 in the KVO, and KVO-CK6 and KVO-CK7 are two parts of KVO-CK4. Therefore, regarding the value of K1-CK2, the requestor can directly refer to the attributes related to the sum of knowledge values in KVO-CK4, KVO-CK6 and KVO-CK7. The knowledge marketable value via aggregation relation function ($MV_{ag}(c_k)$) is shown as Function (10). By applying Function (10) to the example, the value of K1-CK2 is US$155.

$$MV_{ag}(c_k) = \begin{cases} P_{whole} + \sum_{i=1}^{n} P_{part_i} & \text{if} \quad \textit{existing parts}, \quad 1 \leqslant i \leqslant n \\ P_{whole} & \text{if} \quad \textit{no part}, \end{cases} \tag{10}$$

where some CKs (CK_{whole} and CK_{part_i}, $1 \leqslant i \leqslant n$) included in the KVO; CK_{whole} is similar to c_k that is one of the CKs in the evaluated knowledge; CK_{whole} consists of n parts (CK_{part_i}); P_{whole} represents the average transaction price of CK_{whole}; and P_{part_i} represents the average transaction price of each part (CK_{part_i}) of CK_{whole}.

7.3. Association relation model

When CKs are associated with each other, the knowledge values of all dependent concepts must be offered to the requestor as a reference for decision making. In Fig. 5, K1-CK3 is similar to KVO-CK3, which is associated with KVO-CK1. Therefore, the requestor can refer to two concept knowledge units in KVO, i.e. KVO-CK1 and KVO-CK3. The knowledge marketable value via association relation function ($MV_{as}(c_k)$) is shown as Function (11). By applying Function (11) to the example, a set of average transaction prices of KVO-CK3 and KVO-CK1 ({US$80,US$100}) is derived as a result.

$$MV_{as}(c_k) = \begin{cases} P \cup \{P_{as_i} | 1 \leqslant i \leqslant n\} & \textit{if} \quad \textit{existing association relation} \\ P & \textit{if no existing association relation}, \end{cases} \tag{11}$$

where P represents the average transaction price of a CK ck_p in KVO that is similar to c_k; and P_{as_i} $(1 \leqslant i \leqslant n)$ represent the average transaction prices of CKs in KVO that are associated with ck_p.

Concluding the above example of evaluating the marketable value of knowledge K1, K1 has four CKs (K1-CK1, K1-CK2, K1-CK3 and K1-CK4) extracted from the knowledge content of K1. These CKs can represent the knowledge features and classifications of K1. Through the above three functions, the following information related to the marketable value of K1 can be derived as follows: (1) the value of K1-CK1 ranges from US$100-US$120; (2) the value of K1-CK2 is approximately US$155; (3) the value of K1-CK3 can refer to the set of prices {US$80,US$100}; and (4) the value of K1-CK4 is unknown. Such information can help requestors to clarify the rationality of knowledge product price.

8. Implementation and verification

Based on the scenario for knowledge trading activities and the proposed knowledge valuation method, this section designs a k-commerce website framework focusing on knowledge valuation function (Fig. 7). The k-commerce website framework mainly consists of several mechanisms and data bases described below:

- Knowledge Product Uploading Mechanism: Through the web-based supplier interface, knowledge suppliers can upload their knowledge products on the k-commerce platform. Then, the uploaded knowledge is transferred and extended into a knowledge individual ontology, and stored in the Knowledge Product Base.
- Knowledge Requirement Uploading Mechanism: Through the web-based requester interface, knowledge requesters can describe their requirements for knowledge products.
- Knowledge Searching Mechanism: The mechanism offers matching service between knowledge and requirements. Knowledge requesters can utilize the mechanism to find knowledge they need.
- Knowledge Product Representation Mechanism: The mechanism exhibits knowledge product and cooperates with knowledge searching mechanism to show results of knowledge searching.
- Knowledge Trading Execution Mechanism: This mechanism involves activities such as transaction completion, payment on-line, contracting and delegating knowledge usage authority.
- Automatic Knowledge Valuation Support Mechanism: When knowledge uploaded, the mechanism evaluates the knowledge value, which consists of four evaluation components and one knowledge value integration mechanism. The four valuation components, including inventor capability evaluation, supplier reputation evaluation, knowledge innovative degree, and marketable value evaluation, evaluate knowledge values from different aspects and using different sub-methods developed by this study. Knowledge valuation results from the four components are integrated by the knowledge value integration mechanism to support the knowledge searching mechanism and knowledge product representation mechanism for offering complete knowledge product information including knowledge value to help knowledge requesters making decision.
- Expert Knowledge and Experience Valuation Support Mechanism: The mechanism supports more accurate knowledge valuation through the support of experts. The mechanism consists of three components: Expert Selection, Expert Evaluation Support and Knowledge Valuation Conclusion and Integration.

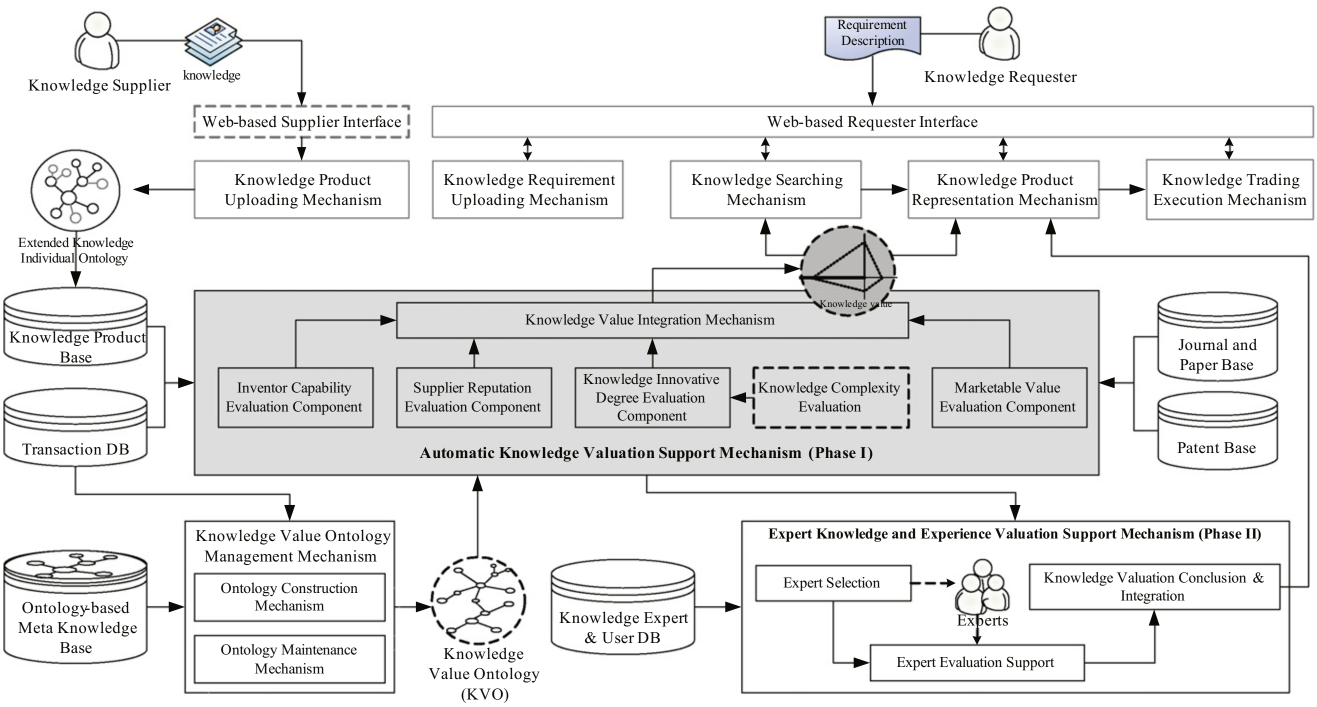

Fig. 7. Knowledge valuation framework.

- Extended Knowledge Individual Ontology (EKIO): Based on some field conceptual knowledge offered by the OMKB, the EKIO generation module transforms the uploaded knowledge into one EKIO, which is a conceptual semantic network consisting of concepts and relationships connecting the concepts. In the EKIO, concepts are transformed from the objects in the knowledge model. The object attributes and features are extracted from the knowledge detailed description, and relationships are transformed from the associations between all classes in the knowledge model.
- Knowledge Product Base: It is used to store all knowledge products and EKIOs.
- Transaction Base: It is used to store all transaction and appraisal data.
- Ontology-based Meta Knowledge Base (OMKB): Some meta knowledge are stored in the base offer knowledge related to industrial domain knowledge and explain concepts and relationships between the concepts.
- Knowledge Expert and User Base: It stores the personal data of all experts and users who buy or sell knowledge, or offer customization knowledge services with other users, via the k-commerce platform.
- Journal and Paper Base: It stores all journal paper information, such as papers, authors and import factors.
- Patent Base: It stores data related to patents.
- KVO Management Mechanism: This mechanism consists of two components: ontology construction mechanism and ontology maintenance mechanism. When a knowledge transaction is complete, the value of the CKs involving the transacted knowledge in the KVO must be maintained by the ontology maintenance mechanism.

At the development phase of the k-commerce platform prototype system, this study first implements the knowledge valuation mechanism. Some diagrams in UML, such as use case, class, activity and sequence diagrams, are used to develop the prototype system at the system analysis and design phase. The k-commerce website is implemented according to the UML diagrams. The website is developed with PHP and equipped with an Apache HTTP Server as web server, and a MySQL as data and knowledge base (DKB) server. The web and DKB servers are run on the Microsoft Windows XP Professional platform. Fig. 8 displays the user interfaces of the k-commerce website, which enables users to search knowledge products. And Fig. 9 shows the result of a knowledge product evaluated by using the knowledge valuation method proposed by this study.

9. Conclusions and future work

k-Commerce features real-time marketing and the delivery of organizational knowledge via the Internet to facilitate the legal and rapid knowledge transfer from owners to consumers. The current k-commerce environment is extremely concerned with the

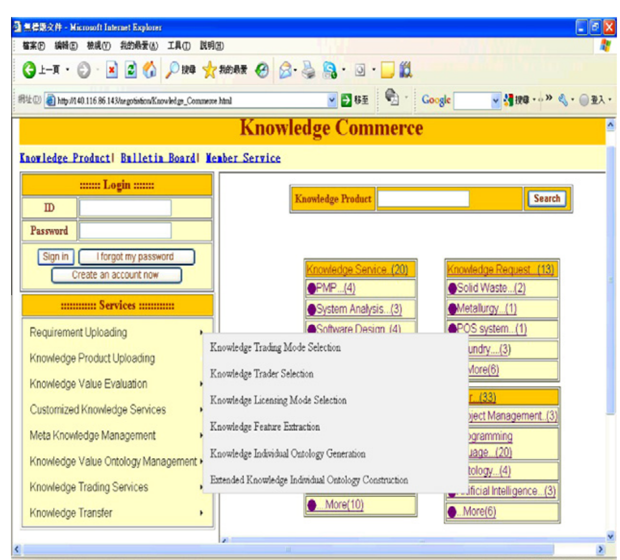

Fig. 8. k-Commerce platform.

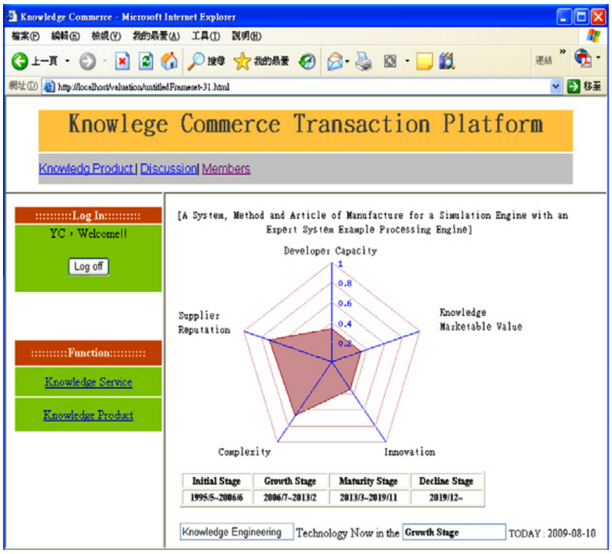

Fig. 9. The result of a knowledge product evaluated.

shortage of automated methods to evaluate effectively the reliability and value of knowledge and its source to provide a valuable reference for the knowledge requestor to make a purchasing decision. Although previous studies acknowledged the importance of this issue, no effective solutions have been proposed until now.

To address this issue, this study develops (1) a knowledge valuation factor model; (2) a knowledge valuation method including four sub-methods; and (3) a k-commerce website framework with the knowledge valuation mechanism to as the core. The knowledge valuation method proposed in this study evaluates the possible values from four aspects, i.e. knowledge inventor capability, knowledge supplier reputation, knowledge innovative degree and complexity, and knowledge marketable value.

Despite not offering a direct, accurate estimation of the actual value of new knowledge, the knowledge valuation method proposed in this study allows one to qualitatively measure the value and quality of knowledge from four different perspectives. In addition to enabling knowledge requestors to make more rational evaluations and accurate decisions, the proposed method also assists knowledge suppliers in achieving more reasonable pricing.

While the proposed method offers a preliminary solution for knowledge valuation, we recommend that future research extends the results of this study in the following ways:

(1) Due to the constraint of access to knowledge product information, this study only includes certain aspects of appraisal factors for evaluation. Future studies should include more aspects in developing related methods;
(2) Studies should be extended to methods for knowledge valuation in Phase II, including those with an expert selection, knowledge valuation conclusion and integration methods; and
(3) A complete k-commerce platform should be constructed, with improvements made in the valuation method accuracy by validation and subsequent improvements for situations involving actual knowledge products.

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