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Evaluation of Knowledge Transfer Efficiency Based on the Synergy of Innovative Clusters

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Abstract

The study was to evaluate efficiency in knowledge transfer for decision support regarding *optimization* and promotion of knowledge transfer under the *synergy of innovation clusters*. The researchers studied the index system of knowledge transfer efficiency evaluation under the synergy of innovation clusters. Based on this, the researchers combined the subjective with objective weighting methods to propose (1) the quantitative weighting method of index weights, and (2) the comprehensive evaluation method of knowledge transfer efficiency. Also based on the actual application case, the researchers verified the proposed *index system* and *evaluation method* for feasibility and effectiveness. The results of the study indicated that a subjective and objective compound weighting method can be used to determine the weight of *the knowledge transfer efficiency index*. The *fuzzy comprehensive evaluation method* made it possible to evaluate knowledge transfer with accuracy and efficiency. Moreover, it was found that the use of a case study can help verify the effectiveness of the index system and evaluation method proposed in this study. It was expected that the reported findings could lay foundation for decision-making for optimization and promotion of knowledge transfer under the synergy of innovation clusters.

Keywords: *knowledge transfer efficiency, innovation clusters, sustainability, innovative methods, knowledge discovery*

1. Introduction

With the continuous development of network and information technology, the increasingly fierce market competition has put the internal and external environment for the survival and development of enterprises in greater complexity and dynamics, and the boundaries of enterprises have become rather blurred and flexible (Ren & Zhang, 2015). In the context of market competition, enterprises need to break through the original organizational boundaries and scale restrictions in the utilization and management of intellectual capital, such as information and knowledge, and lower the information and knowledge barriers between organizations through extensive and in-depth knowledge collaboration with external organizations and enterprises. It is vitally important to build a smooth channel of knowledge exchange and transfer to achieve knowledge sharing and complementarity between organizations (Qi & Dong, 2007). *Innovative clusters* emerged out of the background of such developments. In a specific regional scope or industrial field, innovation clusters are based on the effective aggregation of human resources, information resources, and knowledge resources, and are coordinated with various clusters. Innovation is closely related to the innovation subject, through the role of social capital or relationship capital to form a collaborative relationship. This type of relationship is neither a “one-off” transaction relationship nor an “integration” authority relationship, but *a partnership* based on the principle of “equality, voluntary, long-term, stable, and reciprocal” (Liu, Yuan & Yi, 2012). In the process of *innovation cluster coordination*, the innovation subject realizes the transfer, sharing, and innovation of knowledge resources through this partnership, which effectively promotes the competitive advantage of the innovation cluster, and provides an inexhaustible driving force for the development and growth of the innovation cluster.

In the process of collaborative innovation, the innovation cluster main body realizes sharing, and innovation of knowledge through knowledge transfer, solves the problems encountered in engineering practice, and finally forms collaborative innovation results. In such a process, one of the major concerns focuses on how to attain effective knowledge transfer between innovation subjects and then improve knowledge transfer efficiency for management goals on innovation clusters. In this regard, there has been an acute need *to study the knowledge transfer efficiency of innovation clusters in collaborative innovation.* The evaluation of knowledge transfer efficiency under the synergy of innovation clusters is a complex decision-making issue involving various factors and indicators of knowledge transfer efficiency. Quigley et al. (2007) pointed out that team-oriented incentives, member self-efficacy, self-goal setting, and trust relationship among members are important factors affecting the efficiency of knowledge sharing. Zhang & Zhang (2016) summarized the influencing factors of knowledge flow efficiency into dynamic factors, conditional factors, and capacity factors, namely, four factors of knowledge flow willingness, knowledge flow conditions, knowledge flowability, and network capacity. Wang & Zhang (2013) pointed out that the efficiency of knowledge flow in informal networks shows different changes due to the change of the intensity of the relationship between subjects. When the probability of change in relationship intensity takes a certain value, the knowledge flow shows a high flow rate and high average, the emergence characteristics of the knowledge level and the variance of low knowledge distribution.

Further, regarding the research level of *knowledge transfer efficiency evaluation system and method*, Chen et al. (2017) put forward the evaluation system and method of knowledge sharing efficiency between enterprises from the scope of knowledge authorization and depth. Wu & Pang (2017) evaluated the static knowledge exchange efficiency of the academic community based on the SBM model and studied the dynamic evolution of knowledge exchange in the virtual academic community. Zhu et al. (2017) constructed an evaluation system of practical community knowledge flow efficiency in four aspects: knowledge flow level, knowledge innovation level, knowledge application level, and knowledge perception level. Yang, Hu & Liu (2015), Huang, Zhuang & Yao (2012) used the average knowledge stock, knowledge stock coefficient of variation, and knowledge diffusion speed to measure and evaluate the knowledge sharing efficiency in complex network contexts.

Based on the comprehensive analysis of the above research results, we have found that the research on knowledge transfer mainly focuses on knowledge transfer mode, knowledge transfer influencing factors, and quantitative evaluation methods, *but lacks systematic and in-depth evaluation of knowledge transfer efficiency under the collaborative cluster collaborative situation.* The researchers therefore would like to study knowledge transfer efficiency evaluation under the synergy of innovation clusters; this was to systematically analyze the knowledge transfer efficiency *evaluation index system* under the collaborative cluster collaborative situation, and propose corresponding quantitative evaluation methods of knowledge transfer efficiency in an innovation cluster. It was expected that the cluster enterprises can provide theoretical basis and decision support for knowledge transfer efficiency.

2. Literature Review and Research Analysis

This section deals with literature review and research analysis on (1) the knowledge transfer efficiency evaluation index system under innovation cluster collaboration, and (2) the knowledge transfer efficiency evaluation method.

2.1 Knowledge Transfer Efficiency Evaluation Index System under Innovation Cluster Collaboration

The selection of an *evaluation index* of knowledge transfer efficiency under the synergy of innovation clusters is a complex system. It is necessary to adopt scientific and rational *selection principles and methods,* select the most important knowledge transfer efficiency *evaluation indicators* for analysis and treatment, and finally form a scientific and reasonable *evaluation index*. The system can achieve a comprehensive and accurate evaluation of knowledge transfer efficiency under the synergy of innovation clusters with reasonable accuracy and cost range.

Knowledge transfer is a process in which knowledge subjects are exchanged, acquired, learned, and utilized with knowledge sources through a certain transfer environment or medium to realize knowledge increment and knowledge innovation. Szulanski (1996) asserted that the factors affecting knowledge transfer performance should include five aspects: knowledge transfer *source*, knowledge transfer *recipient*, knowledge transfer *content*, knowledge transfer *approach*, and knowledge transfer *scenario*. Hu (2009) proposed that knowledge sharing evaluation indicators in network organizations should be analyzed in four dimensions: cognitive gaps among network *members*, knowledge-sharing *environment*, knowledge-sharing *coordination behavior*, and knowledge-sharing *results*. From the perspective of knowledge sharing process analysis, Li (2009) divided *the index system* of knowledge sharing efficiency evaluation into three levels: *individual, organization, and platform.* Based on the above research results and thinking, the researchers constructed the knowledge transfer efficiency under the synergy of innovation clusters in four dimensions: knowledge transfer *subject characteristics*, knowledge *content characteristics*, knowledge transfer *environment*, and knowledge transfer *coordination behavior*.

The four dimensions in the evaluation system were explained by the earlier researchers. In the process of innovation cluster coordination, *the knowledge transfer subject* refers to the knowledge sender and the knowledge receiver participating in the knowledge transfer activity; and the knowledge transfer is the knowledge exchange interaction process between the knowledge sender and the knowledge receiver (Han, 2013). Knowledge senders and knowledge recipients can exchange roles for specific knowledge. In the *cluster knowledge* *collaboration*, the knowledge transfer subject has different knowledge types and stocks; there is a knowledge potential difference between the subjects. The knowledge potential difference represents the precondition for knowledge transfer and the driving force of knowledge transfer (Wang, Zhao & Yang, 2009). Willingness of knowledge transfer of knowledge subjects is an important factor for a smooth progress of knowledge transfer. A large number of studies have shown that willingness to transfer knowledge has a significant positive effect on the efficiency of knowledge transfer. The stronger willingness to transfer knowledge, the more active and effective communication and knowledge resource sharing (Chen & Zhao, 2008). The ability of knowledge transfer also has a positive effect on the efficiency of knowledge transfer. The knowledge transferability can be further subdivided into the knowledge sending ability of the knowledge sender and the knowledge absorption ability of the knowledge receiver. The stronger the knowledge transferability of both sides of knowledge transfer, the less difficult and sticky the knowledge transfer, and thus resulting in greater efficiency of knowledge transfer (Li & Li, 2011). On the other hand, the degree of trust and reciprocity between knowledge transfer subjects also have a positive effect on the efficiency of knowledge transfer. Research shows that the degree of trust and reciprocity between knowledge subjects is conducive to the acquisition of new information and new knowledge, and reduced opportunistic behavior and free-riding behavior between subjects (Wang & Huang, 2016). Finally, in the innovation cluster, the embedding of the knowledge transfer subject has a positive impact on the formation of good knowledge cooperation norms between knowledge subjects, which can help the knowledge subjects to acquire more heterogeneous knowledge (Mccall et al., 2008).

Knowledge content refers to the data, information and knowledge exchanged and transferred between the subjects of knowledge transfer (Fang and Wang, 2010). The knowledge in the innovation cluster is the same as general knowledge. It can also be divided into two categories, *explicit* knowledge, and *tacit* knowledge. The degree of explicitness of knowledge largely determines the difficulty of knowledge transfer between knowledge subjects. A large number of studies have shown that there is a significant positive correlation between the degree of explicit knowledge and the efficiency of knowledge transfer (Qu, 2012). The degree of *systematization* of knowledge refers to the extent to which an organization embeds knowledge into organizational processes and norms based on knowledge preservation. The higher the degree of systematization of knowledge, the higher the ability of organizations to absorb and integrate knowledge, and the higher the efficiency of knowledge transfer among knowledge subjects (Peng, 2005). On the other hand, the source and use of knowledge also have an important impact on knowledge transfer. The source of knowledge will determine the content of knowledge to a certain extent. The difficulty of obtaining the source of knowledge will determine the difficulty of knowledge transfer, and thus positively affect the efficiency of knowledge transfer. The use of knowledge determines the search for specific knowledge and the judgment and cognition of the content of knowledge content to a certain extent so that the subject of knowledge has a certain purpose in the process of knowledge-seeking and acquisition. The more they use large and broad knowledge, the more purposeful the initiative of knowledge-seeking, and thus the positive impact on the efficiency of knowledge transfer (Feng & Tian, 2005).

Knowledge transfer takes place in a specific *environment.* The knowledge transfer environment is the basis in support of knowledge management and an important *synergistic factor* for achieving knowledge transfer. Organizational culture is one of the most important environmental factors of knowledge transfer. Whether cluster culture attaches importance to the strategic role of knowledge, whether to encourage open and in-depth knowledge exchange within the cluster has a great impact on the efficiency of knowledge transfer (Ajmal & Koskisen, 2010). Both sides of the knowledge transfer entity have their own institutional and cultural background. The compatibility and matching degree of cognitive structure and management system directly affect the efficiency of knowledge transfer. Similarly, the incentive mechanism of knowledge transfer activities within clusters plays an important role in mobilizing the enthusiasm of knowledge transfer activities and improving the performance of knowledge transfer. Based on this, the fairness of knowledge collaboration procedures and benefit distribution between knowledge transfer subjects is an institutional guarantee to ensure that both partners can carry out deep knowledge collaboration, and it also has a significant impact on knowledge transfer efficiency. Open knowledge exchange, smooth knowledge exchange platform, and diversified knowledge transfer media and channels are important guarantees for the smooth progress of knowledge transfer activities, which reduce the uncertainty and ambiguity of knowledge transfer and ensure the quality effect of knowledge transfer in the form of a positive effect.

Knowledge transfer pays attention to the knowledge and *behavior* activities and interaction *coordination* between enterprises within the cluster. Only by conducting mutual knowledge coordination and coordination behavior can enterprises improve the efficiency of knowledge transfer (Hu, 2009). In the process of innovation cluster coordination, there is a dynamic and complex knowledge exchange relationship between *cluster enterprises*. Therefore, enterprises need to use scientific and reasonable coordination mechanisms to deal with the uncertain knowledge exchange environment to complete complex knowledge collaboration tasks. First of all, the communication between the cluster enterprise managers helps the company to better discover the advantages and disadvantages of both parties, to better exert the knowledge superiority of the enterprise and form the complementary advantages of knowledge collaboration. Therefore, *communication between managers* is an effective means to improve the efficiency of knowledge transfer. Secondly, because a large amount of knowledge in the process of cluster collaborative innovation is *tacit* knowledge, it requires in-depth knowledge exchange and communication between employees of different enterprises. Only through extensive and close communication among employees in the cooperative task can knowledge exchange and transfer be realized. The implementation of the system can create a good knowledge transfer and sharing atmosphere, and thus improve the efficiency of knowledge transfer, especially the transfer efficiency of tacit knowledge (Du et al., 2017). Finally, due to the insufficient information and asymmetry of the cooperative enterprises in the *cluster coordination*, there are cognitive biases in the knowledge transfer problem in cooperation, which requires the constraint and adjustment of the cooperation contract to achieve continuous improvement of knowledge transfer behavior under cluster coordination (Li, 2009).

Based on the above research analysis, *the index system* for evaluating knowledge transfer efficiency under the synergy of innovative clusters is shown in Table 1 below:

Table 1: The Knowledge Transfer Efficiency Evaluation Index System under Innovation Cluster Collaboration

Primary Indicator	Secondary Indicators	Three-level Indicators
Knowledge transfer efficiency	The subject of knowledge transfer	The knowledge gap between knowledge transfer subjects Willingness to transfer knowledge Knowledge transferability Degree of trust between subjects Degree of reciprocity between knowledge transfer subjects Cluster embedding of knowledge transfer subject
	Knowledge content characteristics	Degree of explicit knowledge Systematization of knowledge Source of knowledge Use of knowledge
	Knowledge transfer environment	Knowledge exchange culture within the cluster Institutional compatibility between subjects of knowledge transfer Collaborative procedures and the fairness of benefit distribution Knowledge exchange platform
	Knowledge transfer coordination behavior	Knowledge transfer medium and approach Communication between cluster enterprise managers Communication between employees in cluster enterprises Design and adjustment of cooperation contract

2.2 Knowledge Transfer Efficiency Evaluation Method

As for the efficiency evaluation of knowledge transfer being determined under the cooperation of clusters, the validity of the knowledge transfer efficiency evaluation results mainly depends on two factors: one is the determination of *the weight* of each evaluation index of knowledge transfer efficiency, and the other is the *comprehensive evaluation.* These two factors are explained in two sections 3 and 4.

3. Determination of Weights of Evaluation Indicators Based on Ahp-Entropy Weight Method

In the process of knowledge transfer efficiency evaluation, the determination of index weight is the most important link, and it is also the key to ensure the success of knowledge transfer efficiency assessment. At present, the method for determining the weight of indicators can be divided into two major categories: one is the *subjective* weighting method, including the Delphi method, the ancient forest method, the analytic hierarchy process, the fuzzy comprehensive evaluation method, etc.; the other is the *objective* weighting method, including Deviation maximization method, mean difference method, and threshold method. Both the subject and subjective weighting methods have their advantages and disadvantages and the field of application. The subjective weighting method can evaluate the subjective preference of the subject in a good system, but because the subjective judgment of individuals often differs, the indicators confirmed by this method lack weight stationarity; and the calculation of weights is difficult and the objectivity is poor. In contrast, the weights confirmed by *the objective weighting method* are very objective, but because the amount of information on the main data of the indicators is relatively small, there will be problems with different indicator weights and different truth and importance levels of indicators. Another disadvantage is that the confirmation of the weight will be interfered with by the randomness of the sample data. Different sample data will obtain different weight values (Yang, 2006).

According to the above analysis, the researchers proceeded to use *subjective* composite methods of the ahp method and the entropy weight method to determine the index weight of knowledge transfer efficiency. The evaluation index system of knowledge transfer efficiency under the synergy of innovation cluster has multi-objective and multi-level characteristics, and the evaluation factors carry ambiguity and qualitative characteristics. The use of ahp analytic hierarchy method has the following shortcomings: First, the ahp method is used as the subjective weighting method. When constructing the decision matrix, the evaluator often determines the weight value according to its subjective judgment, so the evaluation result will be the evaluator's experience, self-perception and other errors leading to large differences. Second, the ahp method ignores the situation in which all evaluators assume that a certain indicator is more critical and therefore has a high value; as a result, the weight given by the ahp method is also relatively high, and discriminative power of this indicator is proportionally reduced--leading to the decline of the effectiveness of this evaluation index. In order to solve the above problems in the ahp method, the researchers introduced *the entropy weight method*, an objective weighting method, *to modify the ahp method*, reduce the subjectivity of the weight determined by the ahp method, and appropriately reduce the weights of those indicators with lower discriminative power. The subjective and objective empowerment combined static and dynamic empowerment methods to improve the rationality and effectiveness of the evaluation index weights.

3.1 Ahp Method to Determine the Weight of the Indicator

1) Constructing an evaluation index system

Under the premise of comprehensively grasping the index system of knowledge transfer efficiency evaluation, the relationship between the structure of the indicator system and the indicators at each level is analyzed, and the indicator system is divided into multiple levels, including the target layer, the standard layer, and the indicator layer (Yang, Zhu & He, 2007).

(1) Target layer: There is often only one element in the target layer, which is the main basis for the evaluation of the ahp method. The target layer elements usually represent the issues that need to be addressed or the goals that are expected to be achieved. In this paper, the target layer represents the evaluation of the efficiency of knowledge transfer under the synergy of innovation clusters.

(2) Standard layer: This level contains the central link involved in accomplishing the goal or dealing with the problem. It can be composed of partial levels. The standard layer in this paper represents two four-level indicators for the evaluation of knowledge transformation efficiency of the innovation cluster.

(3) Indicator layer: It can also be called the program layer. It represents the various measures and programs that can be selected to accomplish the goal. It is the visualization of the evaluation target. This paper refers to the indicators in the innovation cluster for the knowledge transfer efficiency evaluation system.

2) Construct a pairwise comparison decision matrix

When constructing the two-two ratio decision matrix, the evaluator first needs to assign a certain scale value to the relative importance of each evaluation index. As shown in Tables 2 and 3, this paper uses a scale of 1-7. The results obtained by comparing the importance of the two elements between the elements to constitute the decision matrix, as shown in Table 4.

Table 2: The Definition of Judgment Matrix

1	Representing the comparison of 2 indicators, with consistent importance.
3	Representing the comparison of two indicators, one indicator is more important than the other.
5	On behalf of the comparison of two indicators, one indicator is more important than the other one.
7	On behalf of two indicators, one indicator is more important than the other.
2，4，6	The median value between the above two separated judgment values.

Table 3: The Definition of Judgment Matrix

1/3	Representing the comparison of two indicators, one indicator is secondary to the other.
1/5	On behalf of the comparison of two indicators, one indicator is more secondary than the other one.
1/7	On behalf of the comparison of two indicators, one indicator is extremely secondary to the other.
1/2，1/4，1/6	Median between the two separated decision values described above.

Table 4: The Judgment Matrix

U	A_1	A_2	……	A_n
A_1	α_{11}	α_{12}	……	α_{1n}
A_2	α_{21}	α_{22}	……	α_{1n}
……	……	……	……	
A_n	α_{n1}	α_{n2}	……	α_{nn}

The decision matrix $A=\left(a_{ij}\right)_{m\times n}$ has the following characteristics:

$$a_{ij}>0 \quad a_{ij}=\frac{1}{a_{ji}} \quad a_{ij}\cdot a_{jk}=a_{ik} \tag{1}$$

3) Calculate the relative importance of the evaluation indicators

The evaluation index relative importance vector $W=(W_1,W_2,\cdots,W_n)^T$ is calculated by:

(1) Seeking law (arithmetic averaging method)

$$W_i=\frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n}a_{kj}},i=1,2,\cdots,n \tag{2}$$

Calculation steps: a. The elements of matrix A are normalized by column, ie $\frac{a_{ij}}{\sum_{k=1}^{n}a_{kj}}$; b. each column after normalization is added; c. dividing the added vector by n Weight vector.

(2) Square root method (geometric average method)

$$W_i=\frac{\left(\prod_{j=1}^{n}a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n}a_{ij}\right)^{\frac{1}{n}}},i=1,2,\cdots,n \tag{3}$$

Calculation steps: a. The elements of matrix A are multiplied by rows to obtain a new vector; b. Each component of the new vector is opened n power; c. The resulting vector is normalized to obtain a weight vector.

(3) Characteristic root method

$$AW = \lambda_{\max} W \tag{4}$$

It can be known from the positive matrix Perron theorem that $\lambda_{\max}$ exists and is unique, and the vector of W is a positive vector, which can be obtained by the power method $\lambda_{\max}$ and the corresponding feature vector W .

4) Consistency test

The consistency index $C.I.$ is calculated according to formulas (7) and (8).

$$C.I. = \frac{\lambda_{\max} - n}{n-1} \tag{5}$$

$$\lambda_{\max} \approx \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{W_i} = \frac{1}{n}\sum_{i=1}^{n}\frac{\sum_{j=1}^{n} a_{ij}W_j}{W_i} \tag{6}$$

Then find the corresponding average random consistency indicator $R.I.$ Table 5 gives the average random consistency index obtained by calculating the $1 \sim 14$ order positive reciprocal matrix 1,000 times.

Table 5: The Average Random Coherence Indexes

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$R.I.$	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54	1.56	1.58

The average random consistency index $R.I.$ is the mean of the consistency index of the same hierarchical random decision matrix. The introduction of $R.I.$ can avoid the disadvantage that the consistency judgment index increases significantly with the increase of n .

Finally, the consistency ratio $C.R.$ is calculated. If it is $C.R. = \frac{C.I.}{R.I.} < 0.1$, the consistency test is passed, and the judgment result obtained is considered to be reasonable.

3.2 Entropy Weight Method to Correct Index Weights

The concept of entropy stems from thermodynamics and was later introduced to information theory by Shannon. According to the definition and principle of entropy, *the entropy value can be used as a measure of the amount of effective information provided by the system*, representing the degree of disorder of a system. The entropy weight method is an objective weighting method combining qualitative and quantitative analysis. The entropy weight method determines the index weight according to the amount of information that each indicator passes to the decision-maker. For the evaluation question, there are m evaluation targets, n evaluation indicators, and the original evaluation matrix $X = (x_{ij})_{m \times n}$ is obtained, and x_{ij} indicates the value of the j evaluation index of the i evaluation object （Xie & Zhong, 2002). Then the entropy value of the j evaluation index x_j

$$\eta_j = -\frac{1}{\ln m}\sum_{i=1}^{m}\kappa_{ij}\ln\kappa_{ij} \tag{7}$$

In the formula $\kappa_{ij} = x_{ij} \Big/ \sum_{i=1}^{m} x_{ij}$, κ_{ij} represents the proportion of the i the part of the target under the j indicator. According to the definition and principle of entropy, the larger the entropy value of an index, the larger the effective information provided by the index, indicating that the less effective information is supplied by this factor, the smaller the function in the system evaluation. The smaller the weight value is, on the contrary, the larger the entropy value, the more effective information the index provides; and the greater the function in the comprehensive evaluation, the greater the weight. The process of correcting the ahp method by the entropy weight method is as follows (Ni et al., 2009):

1) Do a dimensionless processing matrix Y=$(y_{ij})_{m\times n}$ on the X matrix, that is,

$$y_{ij} = \frac{x_{ij}}{\left[\sum_{i=1}^{m} x_{ij}^{2}\right]^{\frac{1}{2}}} \tag{8}$$

i=1,2,3...,m； j=1,2,3...,n 。

i 2) Calculate κ_{ij} , which is the proportion of the j th target indicator.

$$\kappa_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{9}$$

3) Calculate the entropy value η_j of the index j .

$$\eta_j = -\frac{1}{\ln m}\sum_{i=1}^{m}\kappa_{ij}\ln\kappa_{ij},\ (j=1,2,3...,n) \tag{10}$$

Where, $0 \le \eta_j \le 1$.

4) Calculate the difference coefficient χ_j of the j indicator.

$$\chi_j = 1 - \eta_j \tag{11}$$

For the j indicator, the larger the χ_j is, the greater the effect of the indicator on the evaluation of the scheme; conversely, the smaller the χ_j , the smaller the effect of the indicator on the evaluation of the scheme.

5) Calculate the weight w_j of the j indicator.

$$w_j = \frac{\chi_j}{\sum_{j=1}^{n}\chi_j} \tag{12}$$

3.3 Entropy Weight Method Adjusts the Weight of the ahp Method Index

For ahp to obtain the subjective weight of each indicator, the objective w_j obtained by the entropy method has the right to adjust.

$$w''_j = w'_j . w_j \tag{13}$$

Among them, w'_j represents the index weight value obtained by the ahp method.

Normalize the w''_j to get the final adjusted weight W_j .

$$W_j = \frac{w''_j}{\sum_{j=1}^{n} w''_j}, \; j = 1, 2, 3 \ldots n \tag{14}$$

4. Fuzzy Comprehensive Evaluation Method of Knowledge Transfer Efficiency

The evaluation of knowledge transfer efficiency under the synergy of innovation clusters is a very complex and ambiguous system engineering, which contains many problems and factors that are ambiguous and difficult to accurately quantify. It is often difficult to obtain fully sufficient data in the evaluation process. Aiming at this ambiguous feature of knowledge transfer efficiency evaluation, *the researchers intended to use a fuzzy comprehensive evaluation method to comprehensively evaluate the knowledge transfer efficiency under the synergy of innovation clusters.* Specifically, the evaluation of knowledge transfer efficiency under the synergy of innovation clusters is a complex multi-objective comprehensive evaluation problem. Knowledge transfer efficiency evaluation involves multidisciplinary knowledge, such as collaborative innovation theory, cognitive psychology, cluster theory, and knowledge management theory. Besides, when evaluators evaluate the efficiency of knowledge transfer under the synergy of innovation clusters, the comments they use often have some ambiguity. Therefore, this paper proposes the following comprehensive evaluation method of knowledge transfer efficiency under the synergy of innovation clusters; that is, based on the weight of the knowledge transfer efficiency evaluation index determined by the ahp method and the entropy weight method, the fuzzy evaluation matrix is established, and finally, the fuzzy comprehensive evaluation method is used in the innovation cluster for coordinated knowledge transfer efficiency in a comprehensive evaluation.

The calculation process of the fuzzy comprehensive evaluation method is as follows (Tang, 2012):

1) First determine the evaluation level model

(1) Set of factors for evaluating objects

A set of factors is a collection of rating indicators, generally:

$$U = \left(U_1, U_2 \cdots U_n\right) \tag{15}$$

(2) Determine the assessment set v

The evaluation set is a collection of evaluation levels given by the evaluation subject, generally:

$$V = \left(V_1, V_2, \cdots V_q\right) \tag{16}$$

In general, the number of comment levels q is an integer between $[3,7]$. If the q is too large, the evaluation level is difficult to describe, and it is difficult to determine the level of the comment; if the q is too small, the quality requirements of the fuzzy comprehensive evaluation cannot be achieved. Usually, q takes an odd number, so there is an intermediate level to distinguish the rating of the evaluation object. The specific level can be determined by the evaluation expert according to the content and characteristics of the evaluation object and described in an appropriate language.

(3) Establishing a fuzzy mapping relationship between factor set and evaluation set

Establish a fuzzy mapping from u to v, ie:

$$f:U \rightarrow F(V)$$

$$u_i = f(u_i) = m_i = (m_{i1}, m_{i2} \ldots m_{iq}) \tag{17}$$

A single factor evaluation matrix m is obtained.

$$M = \begin{pmatrix} m_{11} & \cdots & m_{1q} \\ \vdots & \ddots & \vdots \\ m_{n1} & \cdots & m_{nq} \end{pmatrix}$$

Among them, m_{ij} is the affiliation of the factor U_i in U and the level V_j in V.

Here, $m_{ij}=$

(4) Determine the evaluation factor weight vector w

Since the factors in the evaluation factor set U are not the same importance to the evaluation object, each factor needs to be given different weights, namely $W=(w_1, w_2, \ldots, w_n)$.

The regulations are:

$$\sum_{i=1}^{n} w_1 = 1, w_i \geq 0, (i=1,2,3,\ldots,n) \tag{18}$$

(5) Select a synthetic operator for the comprehensive evaluation

The basic model of the fuzzy comprehensive evaluation method can be expressed as:

$$R = W \cdot M \tag{19}$$

In the basic formula $R=W \cdot M$ of the fuzzy comprehensive evaluation model, the synthesis of W and M has a very important influence on the final evaluation result, so the selection of the fuzzy synthesis operator "·" is very important. The synthetic operators often used in the fuzzy comprehensive evaluation include main factor determination type, main factor prominent type, unbalanced average type, and weighted average type. The evaluation of knowledge transfer efficiency under the synergy of innovation clusters is a multi-index and multi-level comprehensive evaluation problem, which needs to balance the relative importance of each factor and its impact on the overall evaluation results. Therefore, according to the above analysis, the researchers selected the weighted average type, synthesis operator. Then, by calculation, we got $R=(r_1, r_2, \ldots, r_q)$. If the result of the fuzzy comprehensive evaluation is

$\sum_{i=1}^{n} r_i \neq 1$, , it should be normalized first.

2) Multi-level fuzzy comprehensive evaluation model.

Based on the comprehensive evaluation of the low-level factors, the low-level factor evaluation results are used to comprehensively evaluate the high-level factors. The evaluation process is as follows:

(1) The evaluation factor set U is divided into P subsets, denoted as $U=(U_1,U_2,...,U_p)$, with i subsets $U_i=(U_{i1},U_{i2},...,U_{ik})$,$(i=1,2,3,...,p)$.

(2) For each subset U_i , a comprehensive evaluation is performed according to the first-level model. Let U_i correspond to the weight set W_i , and the U_i corresponding fuzzy evaluation matrix to M_i , then:

$$R_i = W_i \square M_i = (r_{i1}, r_{i2}, ..., r_{im}) \quad (i=1,2,3,...,p) \tag{20}$$

(3) Consider R_i , which is the evaluation of each subset U_i in the factor set U , as P single-level evaluation in U . Set the weight distribution set to W , then the total fuzzy evaluation matrix is:

$$R = \begin{bmatrix} R_1 \\ R_2 \\ ... \\ R_p \end{bmatrix} = (r_{ij})_{pm} \tag{21}$$

The secondary rating results are:

$$R=W \square M \tag{22}$$

The calculation result of the above formula is the comprehensive evaluation result of the factor subset $U_1,U_2,...,U_p$ and the comprehensive evaluation result of all the factors in the evaluation factor set U . The first step to the third step can be repeated several times according to the number of levels until the final satisfactory comprehensive evaluation result is obtained.

5. Application Case

The researchers took the Chongqing electronics industry innovation cluster as the research object and evaluated its knowledge transfer efficiency under the cluster innovation cooperation. The electronics industry is a pillar industry in Chongqing's industrial economy. In 2016, Chongqing's electronics industry surpassed the automobile manufacturing industry and became the first driving force for Chongqing's industrial output growth. The output value was 499.9 billion yuan, contributing more than industrial output growth: 30%, reaching 33.8%. In 2017, the output value increased by 27.5% year-on-year, accounting for 24.1% of the city's industrial output value. The contribution rate to the city's industrial output growth reached 41.3%, becoming the “first catcher” for the steady growth of Chongqing's GDP.

Through the data collection and on-site investigation of mobile phone manufacturers and mobile phone supporting enterprises in the Chongqing electronic industry cluster, the researchers collected the first-hand data and information of knowledge transfer efficiency evaluation. Based on the evaluation index system and comprehensive evaluation method of knowledge transfer efficiency under the innovation cluster proposed in this paper, the process of evaluating and analyzing the knowledge transfer efficiency of Chongqing electronics industry innovation cluster is as follows:

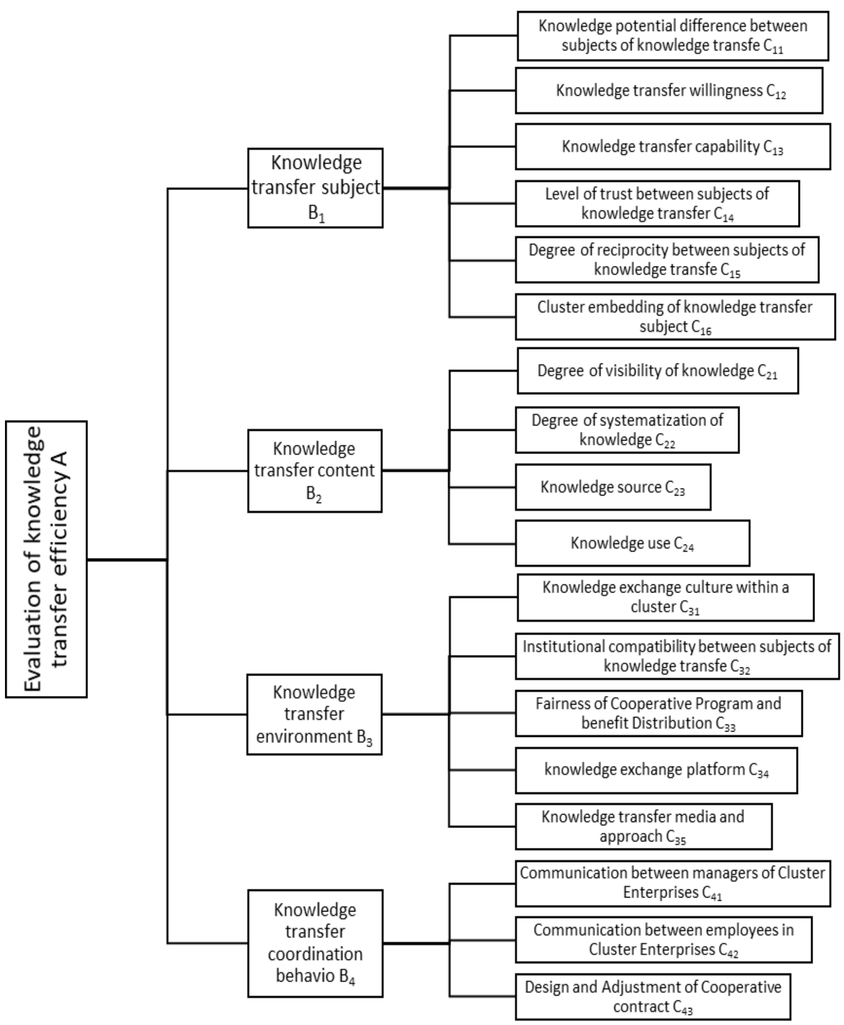
5.1 Knowledge Transfer Efficiency Index Weight Determination

5.1.1 Apply the ahp Method to Determine Subjective Weights

1) The hierarchical structure of the structural evaluation system

According to Section 3 (on entropy weight method adjusts the weight of the ahp method index), the index system of knowledge transfer efficiency under the innovation cluster synergy is proposed, the evaluation indicators are classified, and the hierarchical structure of knowledge transfer efficiency evaluation is constructed, as shown in Figure 1.

Figure 1: The Hierarchical Structure of Knowledge Transfer Efficiency Evaluation



2) Establish a two-two judgment matrix

Based on the knowledge transfer efficiency evaluation hierarchy, seven senior leaders of the backbone enterprises of Chongqing Electronic Industry Cluster, and three experts in the innovation cluster and knowledge management field are invited to compare the importance of the same level of evaluation indicators. The Delphi method is used to judge the relative importance of each index, and then the relative importance of the indicators is evaluated based on the 1-7 scale method. The judgment matrix of each level from high-order indicators to low-level indicators is as follows:

a layer - b layer (level one judgment matrix)

$$A=\begin{array}{cc} A & \begin{matrix} B_1 & B_2 & B_3 & B_4 \end{matrix} \\ \begin{matrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{matrix} & \begin{bmatrix} 1 & 3 & 2 & 4 \\ \frac{1}{3} & 1 & \frac{1}{2} & 2 \\ \frac{1}{2} & \frac{1}{2} & 1 & 1 \\ \frac{1}{4} & \frac{1}{2} & 1 & 1 \end{bmatrix} \end{array}$$

Layer b - layer c (secondary judgment matrix)

$$B_1=\begin{array}{cc} B_1 & \begin{matrix} C_{11} & C_{12} & C_{13} & C_{14} & C_{15} & C_{16} \end{matrix} \\ \begin{matrix} C_{11} \\ C_{12} \\ C_{13} \\ C_{14} \\ C_{15} \\ C_{16} \end{matrix} & \begin{bmatrix} 1 & 1 & \frac{1}{2} & \frac{1}{2} & \frac{1}{3} & 2 \\ 1 & 1 & \frac{1}{2} & \frac{1}{3} & \frac{1}{2} & 3 \\ 2 & 2 & 1 & 2 & 2 & 5 \\ 2 & 3 & \frac{1}{2} & 1 & 2 & 4 \\ 3 & 2 & \frac{1}{4} & \frac{1}{2} & 1 & 6 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{5} & \frac{1}{4} & \frac{1}{6} & 1 \end{bmatrix} \end{array}$$

$$B_2=\begin{array}{cc} B_2 & \begin{matrix} C_{21} & C_{22} & C_{23} & C_{24} \end{matrix} \\ \begin{matrix} C_{21} \\ C_{22} \\ C_{23} \\ C_{24} \end{matrix} & \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{4} & \frac{1}{2} \\ 2 & 1 & \frac{1}{3} & 3 \\ 4 & 3 & 1 & 4 \\ 2 & \frac{1}{3} & 4 & 1 \end{bmatrix} \end{array}$$

$$B_3=\begin{bmatrix} B_3 & C_{41} & C_{42} & C_{43} & C_{44} & C_{45} \\ C_{41} & 1 & 2 & \frac{1}{3} & \frac{1}{2} & \frac{1}{2} \\ C_{42} & \frac{1}{2} & 1 & \frac{1}{4} & 2 & \frac{1}{2} \\ C_{43} & 3 & 4 & 1 & 2 & 2 \\ C_{44} & 2 & \frac{1}{2} & \frac{1}{2} & 1 & \frac{1}{2} \\ C_{45} & 2 & 2 & \frac{1}{2} & 2 & 1 \end{bmatrix}$$

$$B_4=\begin{bmatrix} B_4 & C_{41} & C_{42} & C_{43} \\ C_{41} & 1 & 2 & 1 \\ C_{42} & \frac{1}{2} & 1 & \frac{1}{2} \\ C_{43} & 1 & 2 & 1 \end{bmatrix}$$

3) Solving the judgment matrix by the summation method

Based on the ahp calculation method, the weight set of the first-level indicator can be obtained as:

Wu={0.470,0.172,0.219,0.139}。

Further, the secondary indicator weight set can be obtained as follows:

$W\text{u}_1$={0.104,0.112,0.242,0.239,0.204,0.049}

$W\text{u}_2$={0.100,0.248,0.531,0121}

$W\text{u}_3$={0.125,0.118,0.387,0.135,0.235}

$W\text{u}_4$={0.413,0.260,0.327}。

After verification, the above judgment matrix meets the consistency requirement, thereby ensuring the reliability of the weight vector result.

5.1.2 Applying the Entropy Weight Method to Determine the Objective Weight

1) Build the original datasheet

The electronic industry clusters with a similar situation in the other four provinces and cities and Chongqing's electronics industry clusters were selected and represented by A, B, C, and D, respectively. The researchers organized some field experts to set up an expert group. The expert group graded the evaluation index system proposed in this paper. The score range was 1-5. The higher the score was, the higher the development level of a particular innovation cluster on a certain indicator would be. Finally, the scores of the indicators of the various experts were combined. The obtained raw data are shown in Table 6.

Table 6: The Raw Data Table of Expert Group Scoring

			A		B		C		Ding	
Evaluation on the effect of corporate culture construction *A*	***B*₁**	C_{11}	3	3	4	3	3	2	3	3
		C_{12}		3		3		3		2
		C_{13}		5		4		4		3
		C_{14}		4		3		4		4
		C_{15}		5		4		5		4
		C_{16}		2		2		3		2
	***B*₂**	C_{21}	3	3	4	3	3	4	4	2
		C_{22}		4		2		4		3
		C_{23}		4		4		3		3
		C_{24}		4		3		5		5
	***B*₃**	C_{31}	5	3	4	2	4	3	5	4
		C_{32}		3		4		4		3
		C_{33}		3		3		4		3
		C_{34}		3		3		2		4
		C_{35}		4		3		5		3
	***B*₄**	C_{41}	3	3	2	3	3	5	3	3
		C_{42}		2		4		2		4
		C_{43}		3		4		3		4

2) Determine the objective weight of the entropy weight method

According to the methods and steps given earlier, the objective weights of the primary evaluation indicators are first determined. Table 7 shows the primary data of the primary evaluation indicators.

Table 7: The Raw Data of First-Level Evaluation Index

	B_1	B_2	B_3	B_4
A	3	3	5	3
B	4	4	4	2
C	3	3	4	3
Ding	3	4	5	3

Since the scores in the expert score sheet are all dimensionless data, there is no need to perform dimensionless processing here.

Calculate the proportion p_{ij} of the j innovation cluster indicator, and obtain the weighting table P_{ij} as follows:

Table 8: The Proportion of the ith Innovation Cluster in the jth Index

	B_1	B_2	B_3	B_4
A	0.214	0.214	0.358	0.214
B	0.286	0.286	0.286	0.142
C	0.231	0.231	0.307	0.231
Ding	0.200	0.267	0.333	0.200

According to the formula given earlier, the entropy value, coefficient of variation, and objective weight of each evaluation index are obtained. The results are shown in Table 9.

Table 9: The Entropy, Coefficient of Variation, and Weight of Evaluation Index

	B_1	B_2	B_3	B_4
Entropy value	0.985	0.993	0.991	0.995
Coefficient of variation	0.015	0.007	0.009	0.005
Objective weight	0.417	0.194	0.250	0.139

From the above table, the objective weight w_u of the primary evaluation index = {0.417, 0.194, 0.250, 0.139}.

Further, the objective weights of the secondary evaluation indicators can be obtained as follows:

w_{u1}={0.394,0.081,0.212,0.252,0.061}
w_{u2}={0.241,0.057,0.231,0.161,0.069,0.241}
w_{u3}={0.049,0.138,0.317,0.317,0.114,0.065}
w_{u4}={0.259,0.309,0.061,0.272,0.099}

1 Calculating comprehensive weights using the ahp-entropy weight method

According to the method and steps given earlier, the comprehensive weight of the primary evaluation index is first calculated. According to the formula (15), a_u can be obtained:

$$a_u = W_u . w_u = \{0.470, 0.172, 0.219, 0.139\}.\{0.417, 0.194, 0.250, 0.139\}$$
$$= \{0.196, 0.033, 0.055, 0.019\}$$

Further weights from the formula (16), the combined weights of the primary indicators:

$$\overline{W}_u = \{0.646, 0.109, 0.180, 0.065\}$$

Repeat the above steps to get the comprehensive index weights of the secondary evaluation indicators:

$$\overline{W}_{u1} = \{0.110, 0.125, 0.280, 0.225, 0.198, 0.062\}$$
$$\overline{W}_{u2} = \{0.110, 0.236, 0.527, 0.127\}$$
$$\overline{W}_{u3} = \{0.139, 0.117, 0.368, 0.142, 0.234\}$$
$$\overline{W}_{u4} = \{0.436, 0.217, 0.337\}$$

5.2 Multi-level Fuzzy Comprehensive Evaluation of Knowledge Transfer Efficiency

Determine the innovation cluster knowledge transfer efficiency evaluation level indicator set $U = (U_1, U_2, U_3, U_4)$, the second level indicator set $U_1 = (U_{11}, U_{12}, U_{13}, U_{14}, U_{15}, U_{16})$, $U_2 = (U_{21}, U_{22}, U_{23}, U_{24})$, $U_3 = (U_{31}, U_{32}, U_{33}, U_{34}, U_{35})$, $U_4 = (U_{41}, U_{42}, U_{43})$. The researchers set the evaluation set to v={excellent (4), good (3), qualified (2), unqualified (1)}, and invited seven senior leaders of the key enterprises of Chongqing Electronic Industry Cluster, and innovation. Other three experts in the cluster and knowledge management field also participated in the evaluation. Ten questionnaires were distributed and collected. All ten valid questionnaires were obtained for a statistical analysis. The evaluation results from ten experts are presented in Table 10.

Table 10: The Original Data Table of Judgment Matrix

Index	Evaluation Level			
	Excellent	**Good**	**Qualified**	**Failed**
C_{11}	3	4	2	1
C_{12}	3	4	3	0
C_{13}	4	3	3	0
C_{14}	4	5	1	0
C_{15}	3	3	2	2
C_{16}	4	3	2	1
C_{21}	3	4	2	1
C_{22}	4	3	3	0
C_{23}	2	3	4	1
C_{24}	3	3	3	1
C_{31}	3	4	2	1
C_{32}	3	3	2	2
C_{33}	4	4	2	0
C_{34}	2	4	3	1
C_{35}	2	3	3	2
C_{41}	3	3	3	1
C_{42}	3	2	4	1
C_{43}	2	3	3	2

From the above table, the fuzzy judgment matrix of "the status quo of knowledge transfer efficiency" is:

$$M_{u1}=\begin{bmatrix} \frac{3}{10} & \frac{4}{10} & \frac{2}{10} & \frac{1}{10} \\ \frac{3}{10} & \frac{4}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{3}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{5}{10} & \frac{1}{10} & 0 \\ \frac{3}{10} & \frac{3}{10} & \frac{2}{10} & \frac{2}{10} \\ \frac{4}{10} & \frac{3}{10} & \frac{2}{10} & \frac{1}{10} \end{bmatrix}$$

The fuzzy relation vector R_{u1} is obtained by the first-level fuzzy comprehensive evaluation as follows:

$$R_{u1}=\overline{W}_{u1}\circ M_{u1}$$

$$=\{0.110,0.125,0.280,0.225,0.198,0.062\}\circ\begin{bmatrix} \frac{3}{10} & \frac{4}{10} & \frac{2}{10} & \frac{1}{10} \\ \frac{3}{10} & \frac{4}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{3}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{5}{10} & \frac{1}{10} & 0 \\ \frac{3}{10} & \frac{3}{10} & \frac{2}{10} & \frac{2}{10} \\ \frac{4}{10} & \frac{3}{10} & \frac{2}{10} & \frac{1}{10} \end{bmatrix}$$

$$=\{0.303,0.368,0.218,0.056\}$$

The same is available:

$$R_{u2}=\{0.271,0.311,0.342,0.087\}$$

$$R_{u3}=\{0.299,0.361,0.238,0.098\}$$

$$R_{u4}=\{0.263,0.275,0.318,0.133\}$$

From this, the membership matrix R_u of the second indicator can be obtained.

$$R_u=\left(R_{u1},R_{u2},R_{u3},R_{u4}\right)=\begin{bmatrix} 0.303 & 0.368 & 0.218 & 0.056 \\ 0.271 & 0.311 & 0.342 & 0.087 \\ 0.299 & 0.361 & 0.238 & 0.098 \\ 0.263 & 0.275 & 0.318 & 0.133 \end{bmatrix}$$

Perform a two-level fuzzy comprehensive evaluation to determine the fuzzy comprehensive evaluation vector of the first-level target.

$$R = W_u \cdot R_u = \{0.646, 0.109, 0.180, 0.065\} \cdot \begin{bmatrix} 0.303 & 0.368 & 0.218 & 0.056 \\ 0.271 & 0.311 & 0.342 & 0.087 \\ 0.299 & 0.361 & 0.238 & 0.098 \\ 0.263 & 0.275 & 0.318 & 0.133 \end{bmatrix}$$

$$= \{0.297, 0.355, 0.242, 0.072\}$$

Finally, the total score for evaluating the knowledge transfer efficiency of Chongqing's electronics industry innovation cluster is:

$$S = R \cdot V^T = \{0.296, 0.354, 0.241, 0.071\} \cdot \{4, 3, 2, 1\}^T$$

$$\approx 2.91$$

It can be seen from the above results that the knowledge transfer efficiency level of Chongqing's electronics industry innovation cluster is good. It should be pointed out that the total score of knowledge transfer efficiency evaluation only reflects the knowledge transfer efficiency level of the Chongqing electronics industry innovation cluster as a whole, and it represents that the innovation cluster has reached a good level in all knowledge transfer efficiency indicators. Therefore, the innovation cluster should not only be satisfied with the score of knowledge transfer efficiency evaluation but the application of grade-by-level review and analysis of the knowledge of the two-level and with three indicators in the process of knowledge transfer efficiency evaluation. It should be noted that excellent experience can help form the system, strategy, and method of knowledge transfer. And reports on the existing problems and weak links should need verification prior to realization of the opportunity of the knowledge transfer efficiency measurement, and continuous upgrading of the innovation, knowledge management and competitiveness of the cluster.

6. Conclusion

Aiming at the problem of knowledge transfer efficiency evaluation under the synergy of innovation clusters, the researchers firstly constructed *the knowledge transfer evaluation index system* under the synergy of innovation clusters from the multi-dimensional perspectives of knowledge transfer subject, content, environment, and collaborative behavior, and secondly proposed the ahp-entropy weight method. An *objective and objective compound weighting method* is used to determine the weight of the knowledge transfer efficiency index. Based on the fuzzy comprehensive evaluation method, the accurate and effective evaluation of knowledge transfer efficiency was realized. Finally, the case study of Chongqing was used to verify the effectiveness of the evaluation system and the proposed method. It was expected the findings could help lay the foundation for decision-making for optimization and promotion of knowledge transfer under the synergy of innovation clusters.

7. Conflicts of Interest

The authors declare no conflict of interest in conducting this research.

The authors declare that no competing interests exist.

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The first author Xiaooduo Qian is working for the School of Economics and Business Administration, Chongqing University, Chongqing, China. The second author Xiaofen Liu is currently with the School of Economics and Management, Shihezi University, Shihezi, China. The third author is a lecturer in the BBA Program in International Creative Industry Entrepreneurship, Rattanakosin International College of Creative Entreprenurship, Rajamangala University of Technology Rattanakosin, Thailand. The three researcher-authors have a keen interest in the areas of creative management, evaluation matrices and indices, and synergy of innovative clusters.

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