


## Research Article

# A Multi-Level Fuzzy Comprehensive Evaluation Method for Knowledge Transfer Efficiency in Innovation Cluster

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Knowledge transfer is the essential requirement for innovation clusters to carry out collaborative innovation, and it is a necessary process for innovation clusters to realize the knowledge value enhancement. The evaluation of knowledge transfer efficiency in innovation cluster can effectively reflect the knowledge gap, environment, and whether it is effectively coordinated among members of the innovation cluster. In order to evaluate the knowledge transfer efficiency in innovation clusters more scientifically and accurately, this paper analyzes the main factors affecting the efficiency of knowledge transfer based on the characteristics of innovation clusters and establishes a multi-level comprehensive evaluation system including knowledge transfer subject features, knowledge content features, knowledge transfer environment, and knowledge transfer coordination behavior. Furthermore, a set of AHP-Entropy index weight determination method and multi-level fuzzy comprehensive evaluation method are proposed to evaluate the knowledge transfer efficiency in innovation cluster. The results of the case study show that the evaluation system and method of knowledge transfer efficiency established in this paper are effective, and they can provide valuable reference for the management of knowledge transfer activities in innovation clusters.

## 1. Introduction

With the continuous development of information technology, the increasingly fierce market competition makes the internal and external environment of enterprise greater complexity and dynamism, and the enterprise boundary becomes increasing more blurred and flexible [1]. In the above context, enterprises must break through the original organizational boundaries and scale restrictions in the utilization and management of intellectual capital such as information and knowledge, and break down interorganizational information and knowledge barriers by means of extensive and in-depth knowledge collaboration with external organizations and enterprises [2]. Innovation clusters have emerged from this development context. In a specific regional scope or industrial field, innovation clusters are formed on the premise of effective aggregation of human

resources, information resources, and knowledge resources [3, 4].

In the process of innovation clusters collaboration, the innovation cluster subjects realize transfer, sharing and innovation of knowledge through knowledge transfer, and use it to solve the problems encountered in engineering practice, and finally achieve the collaborative innovation [5, 6]. In this process, how to realize effective knowledge transfer among innovation subjects and improve knowledge transfer efficiency is one of the most important knowledge management issues of innovation clusters. Therefore, it is of great theoretical and practical significance to investigate the knowledge transfer efficiency in the innovation cluster. The evaluation of knowledge transfer efficiency in innovation cluster is a complex decision problem, which needs to consider numerous knowledge transfer efficiency influencing factors and indicators. For the influence of knowledge

characteristics on knowledge transfer efficiency, Zander and Kogut [7] conducted a pioneering study, and they stated that the explicit degree of knowledge determines the efficiency of knowledge transfer to a large extent. Simonin [8] further sublimated Zander and Kogut's findings by proposing multiple internal and external factors of knowledge transfer. Among them, the internal factors are the knowledge transfer subject and the own characteristic attributes of knowledge, and the external factors are the relevant environmental factors of knowledge transfer. Quigley et al. [9] identified team-oriented incentives, member self-efficacy, and self-goal setting and trusting relationship among members as the important factors affecting knowledge sharing efficiency. Luo et al. [10] investigated the co-evolution of complex networks and knowledge sharing based on a multi-intelligence model, and their simulation results showed that factors such as inter-subject knowledge distance, close association, and network cohesiveness had important effects on knowledge sharing efficiency. Regarding the influence of open innovation network features on knowledge transfer efficiency, Su et al. [11] proposed a new measurement method for knowledge transfer efficiency of open innovation network using the weighted complex network theory.

On the other hand, the stream of evaluation method of knowledge transfer efficiency is also very significant. Chen et al. [12] proposed an evaluation system of inter-enterprise knowledge sharing efficiency from two levels of knowledge authorization scope and depth. Wu and Pang [13] evaluated the static knowledge exchange efficiency of academic communities based on the SBM model, and investigated the dynamic evolution of knowledge exchange in virtual academic communities. Zhu et al. [14] constructed an evaluation system of knowledge flow efficiency in practice communities from four aspects: knowledge flow level, knowledge innovation level, knowledge application level, and knowledge perception level. Cowan and Jonard [15], Yang et al. [16], and Li et al. [17] used the average knowledge stock, variation coefficient of knowledge stock, and knowledge diffusion rate to evaluate the knowledge sharing efficiency in the complex network contexts. Regarding the evaluation of knowledge transfer efficiency in the context of innovation clusters, Gai and Dong [18] constructed an evaluation index system of knowledge management efficiency and measured it using the super-efficiency DEA method. From the perspective of knowledge potential difference, Li et al. [19] constructed an evaluation index system of knowledge transfer performance of manufacturing industry innovation clusters, and used AHP-fuzzy set method to comprehensively evaluate the knowledge transfer performance.

Based on the above research, it can be easily found that the current research on knowledge transfer mainly focuses on knowledge transfer models, knowledge transfer influencing factors, and quantitative evaluation methods, while there is a lack of systematic and in-depth research on knowledge transfer efficiency evaluation in the context of innovation cluster. Therefore, this paper intends to conduct an in-depth study on knowledge transfer efficiency evaluation in innovation clusters, systematically analyze the

knowledge transfer efficiency evaluation index system under innovation clusters collaboration, and propose the corresponding quantitative evaluation method of knowledge transfer efficiency, thus providing theoretical basis and decision support for innovation clusters and cluster enterprises to effectively improve knowledge transfer efficiency.

## 2. Evaluation Index System

The selection of knowledge transfer efficiency evaluation indexes under innovation clusters collaboration is a complex systemic issue, which requires the adoption of scientific and reasonable selection principles and methods to select the most important knowledge transfer efficiency evaluation indexes within a reasonable range of evaluation accuracy and cost [20, 21]. Knowledge transfer is the process of knowledge subjects exchanging, acquiring, learning, and utilizing knowledge to knowledge sources through certain transfer environment or medium, and then realizing knowledge increment and knowledge innovation. Szulanski [22] believed that the influencing factors of knowledge transfer performance should contain five elements, including knowledge transfer source, knowledge transfer recipient, knowledge transfer content, knowledge transfer path, and knowledge transfer scenario. Hu [23] proposed that knowledge sharing evaluation indicators in network organizations should be analyzed from four dimensions: cognitive gap among network members, knowledge sharing environment, knowledge sharing coordination behavior, and knowledge sharing results. Drawing on the above research, this paper constructs the evaluation index system of knowledge transfer efficiency in innovation clusters from four dimensions, including knowledge transfer subject features, knowledge content features, knowledge transfer environment, and knowledge transfer coordination behavior. The details of the four dimensions are as follows:

In the process of innovation clusters collaboration, the knowledge transfer subject refers to the knowledge sender and the knowledge receiver involved in knowledge transfer activities, and knowledge transfer is the process of knowledge exchange and interaction between the knowledge sender and the knowledge receiver [24]. For specific knowledge, knowledge senders and knowledge receivers can switch to each other. In innovation cluster, the difference in the types and stocks of knowledge possessed by knowledge transfer subjects leads to knowledge potential differences. Knowledge potential difference is the original driving force of knowledge transfer [25]. Knowledge transfer willingness of knowledge subjects is an important factor for smooth knowledge transfer, and knowledge transfer willingness has a significantly positive effect on knowledge transfer efficiency [26]. The stronger the knowledge transfer willingness, the more proactively, actively, and effectively the knowledge transfer subjects can communicate and share each other's knowledge resources [27, 28]. Knowledge transfer capability likewise contributes positively to knowledge transfer efficiency, which can be further subdivided into knowledge sending capability of the knowledge sender and knowledge

absorbing capability of the knowledge receiver. The stronger the knowledge transfer ability of both sides of knowledge transfer makes knowledge transfer less difficult and sticky, and thus can effectively improve the efficiency of knowledge transfer [29]. On the other hand, the degree of trust and reciprocity among knowledge transfer subjects has a positive contribution to knowledge transfer efficiency. Researchers have shown that the degree of trust and reciprocity among knowledge subjects facilitates the acquisition of new information and knowledge, and reduces opportunistic behavior and free-riding behavior among subjects [30, 31]. Finally, in innovation clusters, the cluster embeddedness of knowledge transfer subjects has a positive impact on the formation of good knowledge cooperation norms among knowledge subjects, which can help knowledge subjects acquire more heterogeneous knowledge [32].

Knowledge content refers to the data, information, and knowledge exchanged and transferred between knowledge transfer subjects. Knowledge in innovation clusters can likewise be divided into two categories, that is, explicit knowledge and tacit knowledge. Explicit degree of knowledge largely determines the difficulty of knowledge transfer among knowledge subjects, and there is a significant positive correlation between the explicit degree of knowledge and knowledge transfer efficiency [33]. Systematization degree of knowledge refers to the extent of knowledge embedding in organizational processes and norms based on knowledge preservation in the organization. The higher systematization degree of knowledge indicates the higher ability of the organization to absorb and integrate knowledge, and the corresponding higher knowledge transfer efficiency among knowledge subjects [34]. On the other hand, the sources and uses of knowledge also have an important influence on knowledge transfer. The source of knowledge will determine the content of knowledge to a certain extent, and the difficulty of acquiring knowledge sources will determine the difficulty of knowledge transfer, thereby affecting the efficiency of knowledge transfer. The usage of knowledge determines the knowledge transfer subject's seeking of specific knowledge and the judgment and cognition of the value of knowledge content to a certain extent, which makes the knowledge subject carry certain purpose in the process of knowledge seeking and acquisition [29, 35].

Knowledge transfer occurs in a specific environment, and the knowledge transfer environment is an important collaborative element to realize knowledge transfer. Organizational culture is a most important environmental factor of knowledge transfer, and whether the cluster culture encourages open and deep knowledge exchange within innovation cluster has a great impact on knowledge transfer efficiency [36, 37]. Each side of the knowledge transfer subject has its own institutional and cultural background, and the compatibility and matching of cognitive structure and management system directly affect the efficiency of knowledge transfer. Similarly, the incentive mechanism of knowledge transfer activities within the cluster plays an important role in mobilizing the motivation of knowledge transfer activities and improving the performance of knowledge transfer. On its basis, the fairness of knowledge collaboration procedures and benefit distribution among

knowledge transfer subjects is the institutional guarantee to ensure the deep knowledge collaboration of both parties, and it also has a significant impact on knowledge transfer efficiency [38]. An open and smooth knowledge exchange platform and diversified knowledge transfer media are important guarantees for the smooth implementation of knowledge transfer activities, which have positive effects on reducing the uncertainty and ambiguity of knowledge transfer and ensuring the quality and effect of knowledge transfer [39].

Knowledge transfer focuses on the knowledge behavior activities and interactive coordination characteristics among cluster internal enterprises, and enterprises can improve the efficiency of knowledge transfer only by conducting mutual knowledge interaction and coordination behaviors. In the process of innovation cluster collaboration, there are dynamic and complex knowledge exchange relationships among cluster enterprises, so enterprises need to apply scientific and reasonable coordination mechanisms to cope with the uncertain knowledge exchange environment. Firstly, communication between cluster enterprise managers helps enterprises better discover the strengths and weaknesses of both sides to better utilize their knowledge advantages, and then form the complementary advantages of knowledge collaboration. Therefore, communication among managers is an effective means to improve knowledge transfer efficiency [40, 41]. Secondly, since 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 from different enterprises. Only through extensive and close communication among employees in common cooperative tasks can the system of knowledge exchange and transfer be put into practice, and a good atmosphere of knowledge transfer and sharing can be created, thus improving knowledge transfer efficiency, especially the transfer efficiency of tacit knowledge [42]. Finally, due to the problems of insufficient and asymmetric information between the two sides of cooperative enterprises in cluster collaboration, there are cognitive biases about the knowledge transfer problem in cooperation, which requires the constraint and adjustment of the cooperation contract to realize the continuous improvement and perfection of knowledge transfer behavior, thereby achieving the purpose of improving the efficiency of knowledge transfer under cluster collaboration [43].

Based on the above comprehensive analysis, the evaluation index system of knowledge transfer efficiency in innovation cluster is constructed as shown in Table 1.

### 3. Knowledge Transfer Efficiency Evaluation Methods

On the premise that the evaluation index system of knowledge transfer efficiency has been determined, the validity and accuracy of the evaluation results of knowledge transfer efficiency mainly depend on two major factors: one is the determination of each evaluation index weight of knowledge transfer efficiency, and the other is the selection of comprehensive evaluation methods.

TABLE 1: Knowledge transfer efficiency evaluation index system in innovation cluster.

Level 1 indicator	Level 2 indicators	Level 3 indicators
		Knowledge potential difference among knowledge transfer subjects $C_{11}$
		Knowledge transfer willingness $C_{12}$
		Knowledge transfer capability $C_{13}$
	Knowledge transfer subject features $B_1$	Trust degree among knowledge transfer subjects $C_{14}$
		Reciprocity degree among knowledge transfer subjects $C_{15}$
		Cluster embeddedness of knowledge transfer subjects $C_{16}$
		Explicit degree of knowledge $C_{21}$
		Systematization degree of knowledge $C_{22}$
Knowledge transfer efficiency $A$	Knowledge content features $B_2$	Sources of knowledge $C_{23}$
		Usage of knowledge $C_{24}$
		Knowledge exchange culture within the cluster $C_{31}$
		Institutional compatibility among knowledge transfer subjects $C_{32}$
	Knowledge transfer environment $B_3$	Fairness of collaboration process and benefit distribution $C_{33}$
		Knowledge exchange platform $C_{34}$
		Knowledge transfer media and channels $C_{35}$
		Communication between cluster enterprise managers $C_{41}$
		Communication between cluster enterprise employees $C_{42}$
	Knowledge transfer coordination behavior $B_4$	Design and adjustment of cooperation contract $C_{43}$

*3.1. Determination of Index Weights.* In the process of knowledge transfer efficiency evaluation, the determination of index weights is the most important step to ensure that knowledge transfer efficiency evaluation can be successful. Currently, the methods of determining index weights can be divided into two main categories [44, 45]: one is the subjective weighting methods, including Delphi method, AHP (Analytic Hierarchy Process), and fuzzy comprehensive evaluation method. The other is the objective weighting method, including maximum deviation method, mean difference method, and threshold method. Both objective and subjective weighting methods have their advantages and disadvantages and areas of application. The subjective weighting method has advantages to evaluate the subjective preference of the subject, but because there are often differences in the subjective judgment of individuals, the index weights confirmed by this type of method lack smoothness. In contrast, because the weights confirmed by the objective weighting method can only have small amount of information based on the main data of the indicators, sometimes there is a problem that the indicator weights are different from the true importance level of the indicators. Another drawback is that the confirmation of the weights suffers from the randomness of the sample data.

Based on the above analysis, this paper intends to use the AHP and entropy weight method jointly with each other to determine the index weights of knowledge transfer efficiency, which is an objective and subjective composite method. The evaluation index system of knowledge transfer efficiency in innovation cluster has the characteristics of multi-objective and multi-level, and the evaluation elements have great fuzzy and qualitative characteristics. The alone application of AHP has the following shortcomings [46]: first, as a subjective weighting method, the AHP method often determines the weight values according to the appraiser's subjective judgment when constructing the judgment matrix, so the appraisal results may vary greatly due to the appraiser's

experience and perception; second, the AHP method ignores the situation that it is assumed that all evaluators think that a certain indicator is critical, and the value given to this indicator is relatively similar, and the weight value given by the AHP method is also relatively high, which makes the recognition of this indicator greatly reduced, and finally leads to the decrease of the effectiveness of this evaluation indicator. To solve the above problems of AHP method, this paper introduces the entropy weight method, an objective weighting method, to amend the AHP method, reduce the subjectivity of the weights determined by the AHP method, and lower the weights of those indicators with low recognition power, so that the subjective and objective weighting methods can be combined with each other to improve the rationality and effectiveness of the evaluation index weights.

### 3.1.1. Overview of AHP Method

- (1) Constructing the hierarchical structure of evaluation index system: on the premise of comprehensively mastering the knowledge transfer efficiency evaluation index system, AHP method firstly analyzes the structure of the index system and the relationship between indicators at each level, and divides the index system into several levels, mainly including the target level, the standard level, and the indicator level.
- (2) Constructing pairwise comparison decision matrix: when constructing the pairwise comparison judgment matrix, the evaluator firstly needs to assign a certain scale value to the relative importance of each evaluation index. As shown in Table 2, this paper applies a scale of 1–7. The results obtained from the pairwise importance comparisons between the elements as shown in Table 3.

The judgment matrix  $A = (a_{ij})_{m \times n}$  has the following properties:

TABLE 2: The definition of judgment matrix.

1	Represents a comparison of 2 indicators that have consistent importance
3	Represents a comparison of 2 indicators, where 1 indicator is more important than the other
5	Represents a comparison of 2 indicators, where 1 indicator is much more important than the other
7	Represents a comparison of 2 indicators, where 1 indicator is extremely important than the other
2, 4, 6	The median value between the above 2 intervening judgment values

TABLE 3: The judgment matrix.

$U$	$A_1$	$A_2$	.....	$A_n$
$A_1$	$\alpha_{11}$	$\alpha_{12}$	.....	$\alpha_{1n}$
$A_2$	$\alpha_{21}$	$\alpha_{22}$	.....	$\alpha_{2n}$
.....	.....	.....	.....	.....
$A_n$	$\alpha_{n1}$	$\alpha_{n2}$	.....	$\alpha_{nn}$

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

(3) Calculating the relative importance of evaluation index: the relative importance vector  $W = (W_1, W_2, \dots, W_n)^T$  of the evaluation index is calculated by the following:

(i) Arithmetic average method:

$$W_i = \frac{1}{n} \sum_{j=1}^n \frac{a_{ij}}{\sum_{k=1}^n a_{kj}}, \quad i = 1, 2, \dots, n. \quad (2)$$

(ii) Geometric average method:

$$W_i = \frac{(\prod_{j=1}^n a_{ij})^{1/n}}{\sum_{i=1}^n (\prod_{j=1}^n a_{ij})^{1/n}}, \quad i = 1, 2, \dots, n. \quad (3)$$

(4) Coherence test:

The coherence index  $C.I.$  is calculated based on the following equations:

$$C.I. = \frac{\lambda_{\max} - n}{(n-1)}, \quad (4)$$

$$\lambda_{\max} \approx \frac{1}{n} \sum_{i=1}^n \frac{(AW)_i}{W_i} = \frac{1}{n} \sum_{i=1}^n \frac{\sum_{j=1}^n a_{ij} W_j}{W_i}. \quad (5)$$

Then, it needs to find the corresponding average random coherence index R.I. Table 4 shows the average random coherence indicators obtained by calculating the 1 ~ 14 rank positive reciprocal matrices 1000 times.

The average random coherence indicator R.I. is the mean value of the coherence indicators of the same rank random judgment matrix, and the introduction of R.I. can circumvent the drawback that the coherence judgment indicator increases significantly with the increase of  $n$  to some extent.

Finally, the coherence ratio  $C.R. = /R.I. < 0.1$ , it passes the coherence test, at which time the obtained judgment result can be considered reasonable.

**3.1.2. Overview of Entropy Weight Method.** The concept of entropy is originated from thermodynamics and 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 a system and represents the degree of disorder of a system. The entropy weight method is an objective weighting method that combines qualitative and quantitative analysis. The entropy weight method determines the indicator weights based on the amount of information that each indicator conveys to the decision maker [47]. For the evaluation problem, with  $m$  evaluation objects and  $n$  evaluation indicators, the original evaluation matrix  $X = (x_{ij})_{m \times n}$  is obtained, and  $x_{ij}$  denotes the value of the  $j$  evaluation indicator of the  $i$  evaluation object. So, the entropy value of the  $j$  evaluation index  $x_j$  can be denoted as follows:

$$\eta_j = -\frac{1}{\ln m} \sum_{i=1}^m \kappa_{ij} \ln \kappa_{ij}, \quad (6)$$

where  $\kappa_{ij} = x_{ij} / \sum_{i=1}^m x_{ij}$ ,  $\kappa_{ij}$  denotes the proportion of the  $i$  participant under the  $j$  indicator. According to the definition and principle of entropy, when the entropy value of an indicator is smaller, it means that the less effective information provided by the indicator, indicating the smaller the function of the indicator in the system evaluation, and the smaller its weight accordingly; on the contrary, the larger the entropy value, the more effective information provided by the indicator, the larger the function in the comprehensive evaluation, and the larger its weight. The correction process of the entropy to the AHP method is shown as follows:

(1) A dimensionless treatment of the  $X$  matrix yields the matrix  $Y = (y_{ij})_{m \times n}$ , that is,

$$y_{ij} = \frac{x_{ij}}{[\sum_{i=1}^m x_{ij}^2]^{1/2}}, \quad (7)$$

$$i = 1, 2, 3, \dots, m; \quad j = 1, 2, 3, \dots, n.$$

(2) Calculate  $\kappa_{ij}$ , which is the weight of the  $j$  indicator of the  $i$  participant.

$$\kappa_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}}. \quad (8)$$

(3) Calculate the entropy value  $\eta_j$  of the  $j$  indicator.

$$\eta_j = -\frac{1}{\ln m} \sum_{i=1}^m \kappa_{ij} \ln \kappa_{ij}, \quad (j = 1, 2, 3, \dots, n), \quad (9)$$

where  $0 \leq \eta_j \leq 1$ .

(4) Calculate the difference coefficient  $\chi_j$  of the  $j$  indicator.

TABLE 4: 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

$$\chi_j = (1 - \eta_j). \quad (10)$$

For the  $j$  indicator, the greater the  $\chi_j$ , the greater the role of the indicator for evaluation; conversely, the smaller the  $\chi_j$ , the smaller the role of the indicator for evaluation.

(5) Calculate the weight  $w_j$  of the  $j$  indicator.

$$w_j = \frac{\chi_j}{\sum_{j=1}^n \chi_j}. \quad (11)$$

**3.1.3. The AHP-Entropy Weight Method.** For the subjective weights of each index obtained by AHP, the weight  $w_j$  obtained by entropy weight method is used to adjust the existing weight.

$$w'_j = w'_j \cdot w_j, \quad (12)$$

where  $w'_j$  represents the index weight value obtained by AHP method.

The final adjusted weights  $W_j$  are obtained by normalizing  $w'_j$ .

$$W_j = \frac{w'_j}{\sum_{j=1}^n w'_j}, \quad j = 1, 2, 3 \dots n. \quad (13)$$

**3.2. Fuzzy Comprehensive Evaluation Method of Knowledge Transfer Efficiency.** Knowledge transfer efficiency evaluation in innovation cluster is a system engineering of great complexity and fuzziness, which contains many issues and factors with fuzziness and difficult to quantify accurately, and it is often difficult to obtain complete and sufficient data and information about the evaluation process. According to this fuzzy characteristic of knowledge transfer efficiency evaluation, this paper intends to apply the fuzzy comprehensive evaluation method to comprehensively evaluate the knowledge transfer efficiency in innovation cluster [48]. In addition, when evaluators evaluate knowledge transfer efficiency under innovation cluster collaboration, the rubric used is often somewhat ambiguous. Therefore, this paper proposes the fuzzy comprehensive evaluation method of knowledge transfer efficiency in innovation cluster: based on determining knowledge transfer efficiency evaluation index weights by using AHP-entropy weight method, establishing fuzzy evaluation matrix, and finally conducting comprehensive evaluation of knowledge transfer efficiency under innovation cluster collaboration by using fuzzy comprehensive evaluation method.

The calculation process of the fuzzy comprehensive evaluation method is as follows.

### 3.2.1. Determining the Evaluation First-Level Model

- (1) Establishing the factor set of the evaluation object  $U$ : the factor set is the set of evaluation indicators, set as  $U = (U_1, U_2 \dots U_n)$ .
- (2) Determining the evaluation set  $V$ : the evaluation set is the set of evaluation levels given by the evaluation subject, set as  $V = (V_1, V_2, \dots V_q)$ .

In general, the rubric level number  $q$  is taken as an integer between [3, 7]. If  $q$  is too large, then it is difficult to describe the evaluation level and to determine the grade of the rubric; if  $q$  is too small, then the quality requirements of fuzzy comprehensive evaluation cannot be achieved. Usually  $q$  is taken as an odd number, so that there is an intermediate grade, which is easy to distinguish the grade of the evaluation object. The specific rank can be determined by the evaluation experts according to the content and characteristics of the evaluation object, and described in appropriate language.

- (3) Establishing the fuzzy mapping relationship between the factor set and the evaluation set: establish a fuzzy mapping from  $U$  to  $V$ , that is,

$$\begin{aligned} f: U &\longrightarrow F(V), \\ u_i &= f(u_i) \\ &= m_i \\ &= (m_{i1}, m_{i2} \dots m_{iq}). \end{aligned} \quad (14)$$

Then, the single-factor judgment matrix  $M$  is obtained.

$$M = \begin{pmatrix} m_{11} & \dots & m_{1q} \\ \vdots & \ddots & \vdots \\ m_{n1} & \dots & m_{nq} \end{pmatrix}, \quad (15)$$

where  $m_{ij}$  is the affiliation of factor  $U_i$  in  $U$  corresponding to the rank  $V_j$  in  $V$ .  $m_{ij}$  is the number of people choosing level  $V_j$  for the  $i$  indicator/total number of people involved in the evaluation

- (4) Determining the evaluation factor weight vector  $W$ : since each factor in the evaluation factor set  $U$  has different importance to the evaluation object, it is necessary to assign different weights to each factor, that is,  $W = (w_1, w_2, \dots, w_n)$ .

The regulations are as follows:

$$\sum_{i=1}^n w_i = 1, \quad w_i \geq 0, \quad (i = 1, 2, 3, \dots, n). \quad (16)$$

- (5) Selecting composite operator for comprehensive evaluation.

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

$$R = W \cdot M. \quad (17)$$

In the basic formula  $R = W \cdot M$  of the fuzzy comprehensive evaluation model, the combination of  $W$  and  $M$  has a very important influence on the final evaluation result, so the selection of fuzzy composite operator “ $\cdot$ ” is very important. The composite operators frequently used in fuzzy comprehensive evaluation include: the principal factor determinant type, the principal factor prominent type, the unbalanced average type, and the weighted average type. Knowledge transfer efficiency evaluation under innovation cluster collaboration is a comprehensive evaluation problem with multiple indicators and multiple levels, which requires a balanced consideration of the relative importance of each factor and its influence on the overall evaluation results. Therefore, based on the above analysis, it is appropriate to choose the weighted average type of composite operator in this paper.

**3.2.2. Multi-Level Fuzzy Comprehensive Evaluation Model.** Based on the comprehensive evaluation of the lower-level factors, the evaluation results of the lower-level factors are used to comprehensively evaluate the higher-level factors.

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

For each subset  $U_i$ , the comprehensive evaluation is conducted by the first-level model separately. Suppose the corresponding weight set of  $U_i$  is  $W_i$  and the corresponding fuzzy evaluation matrix of  $U_i$  is  $M_i$ . There are

$$R_i = W_i \cdot M_i = (r_{i1}, r_{i2}, \dots, r_{im}) \quad (i = 1, 2, 3, \dots, p). \quad (18)$$

Suppose  $R_i$ , which is obtained from the evaluation of each subset  $U_i$  in the factor set  $U$ , as  $P$  single-level evaluations in  $U$ . Then, suppose the weight assignment set is  $W$ , so the total fuzzy evaluation matrix is

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \dots \\ R_p \end{bmatrix} = (r_{ij})_{pm}. \quad (19)$$

Finally, the second-level evaluation results are

$$R = W \cdot M. \quad (20)$$

## 4. Case Study

This section takes mobile phone industry innovation cluster of Chongqing, China as the research object to evaluate its knowledge transfer efficiency under the cluster innovation collaboration. At present, there are 116 mobile-phone enterprises and 138 mobile-phone supporting enterprises in mobile phone industry innovation cluster of Chongqing, and the output value of the mobile-phone industry exceeds 100 billion yuan. Through data collection and on-site research on mobile phone manufacturer enterprises in Chongqing mobile phone industry cluster, this paper collects the first-hand data and information of knowledge transfer efficiency evaluation. Based on the index system and comprehensive evaluation method of knowledge transfer efficiency under innovation cluster collaboration proposed in this paper, the process of evaluating and analyzing the knowledge transfer efficiency of the innovation cluster of Chongqing mobile phone industry is shown as follows.

**4.1. Application of AHP Method to Determine Subjective Weights.** Based on the evaluation index system of knowledge transfer efficiency, senior leaders of backbone enterprises of Chongqing mobile phone industry cluster (7 persons) and experts in innovation cluster and knowledge management (3 persons) are invited to make pairwise comparison of the importance of evaluation indexes at the same level, judge the relative importance of each index using the Delphi method, and then evaluate the relative importance of the indexes, and establish a judgment matrix at all levels from high-level indexes to low-level indexes as shown below:

Layer A-Layer B (First level judgment matrix):

$$A = \begin{bmatrix} A & B_1 & B_2 & B_3 & B_4 \\ B_1 & 1 & 3 & 2 & 4 \\ B_2 & \frac{1}{3} & 1 & \frac{1}{2} & 2 \\ B_3 & \frac{1}{2} & \frac{1}{2} & 1 & 1 \\ B_4 & \frac{1}{4} & \frac{1}{2} & 1 & 1 \end{bmatrix}. \quad (21)$$

Layer B-Layer C (Second level judgment matrix):

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

$$B_2 = \begin{bmatrix} B_2 & C_{21} & C_{22} & C_{23} & C_{24} \\ C_{21} & 1 & \frac{1}{2} & \frac{1}{4} & \frac{1}{2} \\ C_{22} & 2 & 1 & \frac{1}{3} & 3 \\ C_{23} & 4 & 3 & 1 & 4 \\ C_{24} & 2 & \frac{1}{3} & 4 & 1 \end{bmatrix}, \quad (22)$$

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

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

Using AHP, the weight sets of first-level indicators can be obtained as

$$W_u = \{0.470, 0.172, 0.219, 0.139\}.$$

Further, second-level indicator weight sets can be obtained as follows:

$$W_{u1} = \{0.104, 0.112, 0.242, 0.239, 0.204, 0.049\},$$

$$W_{u2} = \{0.100, 0.248, 0.531, 0.121\},$$

$$W_{u3} = \{0.125, 0.118, 0.387, 0.135, 0.235\},$$

$$W_{u4} = \{0.413, 0.260, 0.327\}.$$

The above judgment matrix is tested to meet the consistency requirements, thus ensuring the reliability of the weight vector results.

*4.2. Application of Entropy Weight Method to Determine Objective Weights.* This paper selects the mobile phone industry clusters in other four provinces and cities which are similar to mobile phone industry cluster of Chongqing, and express them as A, B, C, and D, respectively. Several experts in the related field are organized to set up an expert panel, and the expert panel scores the evaluation indicator system with the score range of 1–5. The higher the score indicates, the higher the development level of a specific innovation cluster on a certain indicator. Finally, the scoring results of each expert on the indicator system are combined to obtain the raw data in Table 5.

According to AHP method, the objective weights of the first-level evaluation indicators are first determined, and the raw data of the first-level evaluation indicators can be seen from Table 6.

The weight  $p_{ij}$  of the  $j$  indicator of the  $i$  innovation cluster is calculated, and the weight table  $P_{ij}$  is obtained as shown in Table 7.

Furthermore, the entropy value, variation coefficient, and objective weight of each evaluation indicator are obtained in Table 8.

From the above table, the objective weights of the first-level evaluation indicators  $w_u = \{0.417, 0.194, 0.250, 0.139\}$ .

Further, the objective weights of the second-level evaluation indicators can be obtained as follows:

$$W_{u1} = \{0.394, 0.081, 0.212, 0.252, 0.061\},$$

$$W_{u2} = \{0.241, 0.057, 0.231, 0.161, 0.069, 0.241\},$$

$$W_{u3} = \{0.049, 0.138, 0.317, 0.317, 0.114, 0.065\},$$

$$W_{u4} = \{0.259, 0.309, 0.061, 0.272, 0.099\}.$$

*4.3. Using AHP-Entropy Weight Method to Calculate the Comprehensive Weight.* The comprehensive weights of the first-level indicators can be obtained by (13).

$$\bar{W}_u = \{0.646, 0.109, 0.180, 0.065\}. \quad (23)$$

Repeating the above steps, the comprehensive indicator weights of the second-level evaluation indicators can be obtained as follows:



TABLE 5: The raw data of expert scoring.

		A	B	C	D		
Knowledge transfer efficiency evaluation A	<b>B<sub>1</sub></b>	C <sub>11</sub>	3		3	2	3
		C <sub>12</sub>	3		3	3	2
		C <sub>13</sub>	5	4	4	4	3
		C <sub>14</sub>	4	4	3	4	3
	<b>B<sub>2</sub></b>	C <sub>15</sub>	5		4	5	4
		C <sub>16</sub>	2		2	3	2
		C <sub>21</sub>	3		3	4	2
		C <sub>22</sub>	4	4	2	4	3
	<b>B<sub>3</sub></b>	C <sub>23</sub>	4		4	3	3
		C <sub>24</sub>	4		3	5	5
		C <sub>31</sub>	3		2	3	4
		C <sub>32</sub>	3		4	4	3
	<b>B<sub>4</sub></b>	C <sub>33</sub>	5	4	3	4	5
		C <sub>34</sub>	3		3	2	4
		C <sub>35</sub>	4		3	5	3
		C <sub>41</sub>	3		3	5	3
<b>B<sub>4</sub></b>	C <sub>42</sub>	3	2	4	3	2	
	C <sub>43</sub>	3	2	4	3	3	

TABLE 6: The raw data of first-level evaluation index.

	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>	B <sub>4</sub>
A	3	3	5	3
B	4	4	4	2
C	3	3	4	3
D	3	4	5	3

TABLE 7: The proportion of the *j* index in the *i* innovation cluster.

	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>	B <sub>4</sub>
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
D	0.200	0.267	0.333	0.200

TABLE 8: The entropy value, variation coefficient, and weight of evaluation index.

	B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>	B <sub>4</sub>
Entropy value	0.985	0.993	0.991	0.995
Variation coefficient	0.015	0.007	0.009	0.005
Objective weight	0.417	0.194	0.250	0.139

$$\begin{aligned}
 \bar{W}_{u1} &= \{0.110, 0.125, 0.280, 0.225, 0.198, 0.062\}, \\
 \bar{W}_{u2} &= \{0.110, 0.236, 0.527, 0.127\}, \\
 \bar{W}_{u3} &= \{0.139, 0.117, 0.368, 0.142, 0.234\}, \\
 \bar{W}_{u4} &= \{0.436, 0.217, 0.337\}.
 \end{aligned}
 \tag{24}$$

4.4. Multi-Level Fuzzy Comprehensive Evaluation of Knowledge Transfer Efficiency. Based on the multi-level fuzzy comprehensive evaluation method, this paper determines the first-level index set as  $U = (U_1, U_2, U_3, U_4)$  and the second-level index set as  $U_1 = (U_{11}, U_{12}, U_{13}, U_{14}, U_{15}, U_{16})$ ,  $U_2 = (U_{21}, U_{22}, U_{23}, U_{24})$ ,  $U_3 = (U_{31}, U_{32}, U_{33}, U_{34}, U_{35})$ ,

$U_4 = (U_{41}, U_{42}, U_{43})$ . In this paper, the judgment set is defined as  $V = \{\text{excellent (4), good (3), qualified (2), unqualified (1)}\}$ , and senior leaders of the backbone enterprises of Chongqing mobile phone industry cluster (7 people) and experts of innovation cluster and knowledge management field (3 people) are again invited to participate in the evaluation. Then, the fuzzy judgment matrix of “current situation of knowledge transfer is obtained as follows:

$$M_{u1} = \begin{bmatrix} \frac{3}{10} & \frac{4}{10} & \frac{2}{10} & \frac{1}{10} \\ \frac{3}{10} & \frac{4}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{3}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{5}{10} & \frac{1}{10} & 0 \\ \frac{3}{10} & \frac{3}{10} & \frac{2}{10} & \frac{2}{10} \\ \frac{4}{10} & \frac{3}{10} & \frac{2}{10} & \frac{1}{10} \end{bmatrix}.
 \tag{25}$$

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

$$\begin{aligned}
R_{u1} &= \bar{W}_{u1} \cdot M_{u1} \\
&= \{0.110, 0.125, 0.280, 0.225, 0.198, 0.062\} \\
&= \begin{bmatrix} \frac{3}{10} & \frac{4}{10} & \frac{2}{10} & \frac{1}{10} \\ \frac{3}{10} & \frac{4}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{3}{10} & \frac{3}{10} & 0 \\ \frac{4}{10} & \frac{5}{10} & \frac{1}{10} & 0 \\ \frac{3}{10} & \frac{3}{10} & \frac{2}{10} & \frac{2}{10} \\ \frac{4}{10} & \frac{3}{10} & \frac{2}{10} & \frac{1}{10} \end{bmatrix} \\
&= \{0.303, 0.368, 0.218, 0.056\}.
\end{aligned} \tag{26}$$

Similarly, we can obtain

$$\begin{aligned}
R_{u2} &= \{0.271, 0.311, 0.342, 0.087\}, \\
R_{u3} &= \{0.299, 0.361, 0.238, 0.098\}, \\
R_{u4} &= \{0.263, 0.275, 0.318, 0.133\}.
\end{aligned} \tag{27}$$

Therefore, the affiliation matrix  $R_u$  of the second-level indicators can be obtained as follows:

$$\begin{aligned}
R_u &= (R_{u1}, R_{u2}, R_{u3}, R_{u4}) \\
&= \begin{bmatrix} 0.303 & 0.368 & 0.218 & 0.056 \\ 0.271 & 0.311 & 0.342 & 0.087 \\ 0.299 & 0.361 & 0.238 & 0.098 \\ 0.263 & 0.275 & 0.318 & 0.133 \end{bmatrix}.
\end{aligned} \tag{28}$$

A second-level fuzzy comprehensive evaluation is performed to determine the fuzzy comprehensive evaluation vector for the first-level objective.

$$\begin{aligned}
R &= W_u \cdot R_u \\
&= \{0.646, 0.109, 0.180, 0.065\} \\
&= \begin{bmatrix} 0.303 & 0.368 & 0.218 & 0.056 \\ 0.271 & 0.311 & 0.342 & 0.087 \\ 0.299 & 0.361 & 0.238 & 0.098 \\ 0.263 & 0.275 & 0.318 & 0.133 \end{bmatrix} \\
&= \{0.297, 0.355, 0.242, 0.072\}.
\end{aligned} \tag{29}$$

Finally, the total evaluation score of knowledge transfer efficiency of Chongqing mobile phone industry innovation cluster is obtained:

$$\begin{aligned}
S &= R \cdot V^T \\
&= \{0.296, 0.354, 0.241, 0.071\} \cdot \{4, 3, 2, 1\}^T \\
&\approx 2.91.
\end{aligned} \tag{30}$$

Based on the above results, the knowledge transfer efficiency level of the Chongqing mobile phone industry innovation cluster belongs to the good level. It should be noted that the total knowledge transfer efficiency evaluation score only reflects knowledge transfer efficiency level of Chongqing mobile phone industry innovation cluster on a whole, but it does not mean that the innovation cluster has achieved good level in all knowledge transfer efficiency indicators. Therefore, innovation clusters should not only be satisfied with knowledge transfer efficiency evaluation scores, but also review and analyze the advantages and disadvantages of each second-level and even third-level indicator scores in the process of knowledge transfer efficiency evaluation step by step, find and summarize the excellent experiences and problematic shortcomings among them, and form knowledge transfer systems, strategies and methods from the excellent experiences, and carry out special remediation and improvement for the problems and weak links among them, so as to continuously improve the knowledge management level and innovation competitiveness of innovation clusters by taking the knowledge transfer efficiency evaluation as an opportunity.

## 5. Conclusion

Efficiency evaluation of knowledge transfer is an important issue of knowledge management of innovation clusters, which can enable the managers of innovation clusters to accurately recognize the knowledge transfer status. This paper evaluated the knowledge transfer efficiency in innovation clusters from the perspective of systems engineering, and comprehensively considered the characteristics of the environment, subject, relationship, and knowledge of innovation clusters. Then, a multi-level comprehensive evaluation system is constructed, which includes Knowledge transfer subject features, Knowledge content features, Knowledge transfer environment, and Knowledge transfer coordination behavior. As for the evaluation method, according to the characteristics of the combination of qualitative and quantitative evaluation indicators, an AHP-entropy method of index weight is further proposed. Moreover, considering the uncertainty and ambiguity of the evaluation of knowledge transfer efficiency in innovation clusters, a comprehensive fuzzy evaluation method of multi-level model is used to comprehensively evaluate the knowledge transfer efficiency in innovation clusters. Through the empirical analysis on the knowledge efficiency in Chongqing smartphone innovation cluster, the validity and practicability of the evaluation system and evaluation method proposed in this paper are tested. This paper can

provide a feasible research reference for investigating the mechanism of knowledge transfer behavior in innovation clusters from the perspective of systematic knowledge management, and evaluating and measuring the development trend of knowledge transfer in innovation clusters. However, how to reflect the individual differences of knowledge subjects and the transfer time delay in the knowledge transfer of innovation clusters is still a problem that needs to be further solved, and it is also an important direction for further exploration.

### Data Availability

The data used to support the findings of this study are included within the article.

### Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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