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Applying a Hybrid Multiple Attribute Decision-Making Model to Evaluate the Improvement Strategy for Effective Technology Transfer Modes

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ABSTRACT

With the unprecedented growth of technological advancement, effective technological transfer has become increasingly important in all dimensions of human lives. Technological transfer is a multi-level and complex ecosystem network with complicated inter-relational elements and effective factors. This complexity raises the question of how to rearrange the elements of the technology transfer to improve its positive performance. To address this issue, this study aims to compare the performance and gaps of the three modes of technology transfer, which are technology entrepreneurship, technology licensing, and technology shareholding, by evaluating the three participants, which are universities/research institutes, corporations, and intermediary agencies, using related attributes. This study applies a hybrid multiple attribute decision-making (HMADM) model including the DEMATEL for constructing the INRM, DANP for computing influence weights, modified VIKOR for evaluating the performances and gaps among the three technology transfer modes so that to develop sustainable and systemic improvement strategies. At the macro level, the results show that, the technology transfers modes receive an overall positive effect, especially universities/research institutions. At the micro level, the technology licensing has not only the highest performance but also the largest gap. According to this finding, technology licensing is the most feasible way to cater to technology transfer at the macro level from the micro level. The findings suggest decision makers pay attention to the role of universities/research institutes as the main factor influencing technology transfer effectiveness. Also, they should focus on influential attributes such as researcher participation and technical collaboration ability for reducing the gap.

Keywords: technology transfer, ecosystem network, improvement strategies, HMADM, technology licensing

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1. Introduction

With the rapid development of the world economy, the birth of a large number of high-precision and sharp technology, the more and more intense competition between enterprises, but also make the enterprises and even the country has a strong demand for high and new technology [1-2]. Science and technology promote the development of social economy, and the continuous progress of social economy is also continuously putting forward higher requirements for science and technology [3-4]. Technology transfer is a key factor in realizing enterprise development and structural adjustment, and an important aspect in promoting the modernization of development enterprises [5]. With the spillover effects of advanced technologies, urbanization and consumer purchasing power and the gradual increase in consumer demand for high-value and differentiated products, the convenience, diversity, branding and sustainability of product quality in enterprises have become increasingly important [6-9]. Due to poor capital flows and imperfect technology transfer markets for Chinese SMEs, firms are not only facing the challenge of meeting new consumer requirements, but also the risk of marginalization [10-12]. Although SMEs utilize various forms of introducing and utilizing interrelated technologies for vertical transfer to overcome technological constraints and achieve the purpose of improving the production level of enterprises, there are still many technologies that cannot be transferred effectively [13-15]. Accompanied by the continuous deepening of the construction process of innovative countries, the situation of technology transfer in China has changed dramatically, establishing a new mechanism to act on the basis of the existing technology in the economy and society, playing the main role of social enterprises to a certain extent, and increasing the awareness of technology research and development to serve the development of society [16-19]. However, technology transfer is a complicated task, how to take effective means to continuously enhance the capacity of technology transfer and promote sustainable economic development is the current national governance needs to pay attention to the problem.

This study aims to investigate whether the 3 groups of technology transfer affect the modes of technology transfer and sustainable development positively or negatively. To this end, this study measures the effects of the 3 groups of technology transfer using 12 various attributes on the 3 different modes. Then, this research compares the efficiency of the 3 groups and modes in a comprehensive and innovatively comparative analysis. The 3 different groups are intermediary agencies service, corporations, and universities/research institutes. The 3 modes of technology transfer are autonomous technology entrepreneurship, technology licensing, and technology shareholding. The 12 various attributes are technology readiness, technology embeddedness, researcher participation, institutional arrangements, demand for new technology, relationship with technology supplier, learning ability, management ability, assessment ability, communication ability, technical collaboration ability, and operational assistance ability.

Innovatively, this research develops a Hybrid Multiple Attribute Decision-Making (HMADM) model by combining Decision-Making Trial and Evaluation Laboratory (DEMATEL), DEMATEL-based- Analytic Network Process (DANP), and modified VIKOR (Vise I Kriterijumska Optimization Komproisno Resenje in Serbian language) (MV).

The findings of the study can provide insights into the factors (*i.e,* attributes) that affect the efficiency and effectiveness of technology transfer. The study identifies the strengths and weaknesses of each mode, group, and attribute and provides a ranking based on their efficiency and effectiveness. As a practical contribution, this information can be used by policymakers, technology transfer managers, and entrepreneurs to make informed decisions about the most appropriate mode of technology transfer for different conditions and cases. As a theoretical contribution, the HMADM model developed in this study can be used as a framework for future research in this area and can also serve as a useful tool for decision-making in the technology transfer process.

The rest of this paper is organized as follows. The next section reviews the previous studies to express the research gap. Then, Section 3 is the methodology section, proposing the HMADM model in terms of the DEMATEL, D-DANP, and MV formulations. The section also highlights the factors that influence technology transfer and provides a list of the attributes for constructing the evaluating system. Section 4 explains the process of data collection and attribution setting, results presenting an empirical case to illustrate how the HMADM model can identify the role and importance of each of these attributes in technology transfer. Also, identifies and compares the performance and gaps for alternative technology transfer modes. Then, the discussion section which argues the main findings. Finally, Section 5 represents the conclusion and remarks which concludes the paper and offers a few suggestions for future studies.

2. Methodology

This research uses a Hybrid Multiple Attribute Decision-Making (HMADM) model to compare the 3 modes of technology transfer. To construct this model, this study combines Decision-Making Trial and Evaluation Laboratory (DEMATEL), DEMATEL-based- Analytic Network Process (DANP), and modified VIKOR (Vise I Kriterijumska Optimization Komproisno Resenje in Serbian language) (MV).

The developed HMADM model compares the effectiveness of 3 main technology transfer modes by measuring the effectiveness of 12 attributes based on the questionnaire responded by 3 different groups of people. The 3 modes of technology transfer are autonomous technology entrepreneurship, technology licensing, and technology shareholding. The 12 various modes are technology readiness, technology embeddedness, researcher participation, institutional arrangements, demand for new technology, relationship with technology suppliers, learning ability, management ability, assessment ability, communication ability, technical collaboration ability, and operational assistance ability. The 3 different groups are intermediary agencies service, corporations, and universities/research institutes.

The proposed model is capable of simultaneously analyzing complex influence relationships among hierarchical levels of multi-participants with related attributes (i.e., successful factors). The existing decision methods are unable to have a simultaneous and comprehensive analysis of interlinkages of the attributes and the performance of the modes. However, the HMADM part of the model, in particular, can overcome the limitations of existing decision models and analyze the main attributes affecting the technology transfer and the performance with the technology transfer modes. Armed with the analytical power of HMADM, this study evaluates the interdependence of the attributes that affect technology transfer. The evaluation can, then, be used to construct improvement strategies that can achieve the desired levels of performance from a certain technology transfer mode.

2.1. *HMADM in a technical description*

The HMADM model proposed in this study is a hybrid technique that follows three stages to combine three different techniques. Figure 1 displays the conceptual framework of this model. According to Figure 1, the HMADM model uses the DEMATEL technique which constructs the influential network relationship map (INRM) with the attributes of technology transfer collected from related references and selected by experts with their experiences in the first stage. In the second stage, the DEMATEL-based analytic network process (DANP) computed the interrelation influential weights (IWs) according to the DEMATEL technique outcomes that become D-DANP. Finally, the third stage applies the modified VIKOR (MV) to evaluate the performances of technology transfer modes by the IWs of the attributes computed by D-DANP forming the D-DANP-MV.

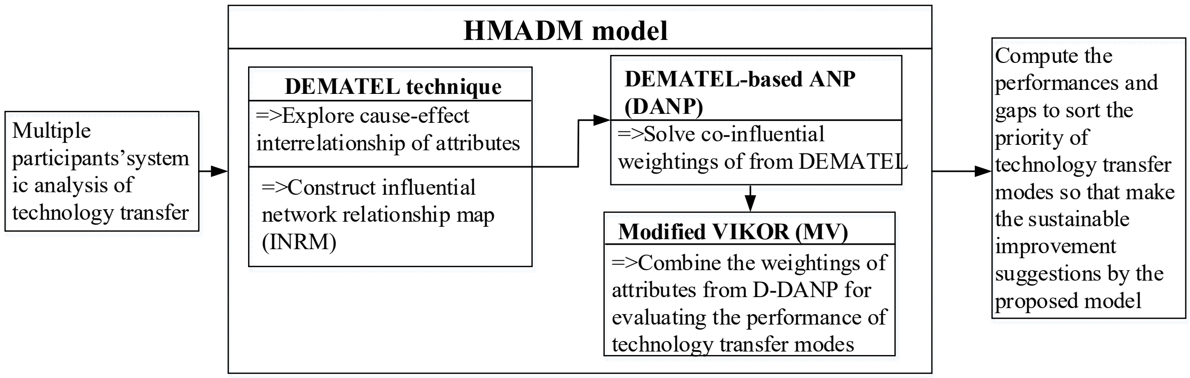

Fig. 1. Conceptual framework of the Hybrid Multiple Attribute Decision-Making (HMADM) model in this study

2.2. DEMATEL technique

This stage uses the experts' responses in the Decision-Making Trial and Evaluation Laboratory (DEMATEL) to provide INRM including x and y vectors. These vectors are the results of the matrices constructed by the experts' responses. The horizontal axis vector is ($x_i + y_i$) illustrating the influencing character of the criterion. Similarly, the vertical axis vector is ($x_i - y_i$), showing the influenced measures. When ($x_i - y_i$) is positive, the criterion is part of the causal group, that is, criterion i affects other attributes. By contrast, if ($x_i - y_i$) is negative, the criterion is part of the affected group, that is, criterion i is influenced by other attributes. Mapping the data set ($x_i + y_i, x_i - y_i$) will lead to a graph called INRM. This technique has four steps, described in detail in the appendix. This technique finally provides the INRM including x and y vectors with the above characters.

2.2.1. DEMATEL steps. The DEMATEL has four steps and is an effective technique for identifying critical success factors in a particular situation. This technique is widely applied to various areas such as improving a search engine, evaluating the financial performance of a company, enhancing mobile banking services, or assessing information security risk. The four steps of this technique are as follows.

Step 1: Calculate the direct-influence matrix by scores.

Using a scale ranging from 0 to 4, experts assess the relationship between mutual influence criteria. These scores represent: 'absolutely no influence' (0), 'low influence' (1), 'medium influence' (2), 'high influence' (3), and 'very high influence' (4). The experts are required to indicate the direct influence by a pairwise comparison. If they believe that criterion i influences criterion j, they should indicate it by d_c^{ij}. Putting the information together yields matrix $\boldsymbol{D} = [d_c^{ij}]_{n \times n}$ of direct relationships (see Eq. (1)). All diagonal elements are set to zero by convention.

$$\boldsymbol{D} = \begin{bmatrix} d_c^{11} & \cdots & d_c^{1j} & \cdots & d_c^{1n} \\ \vdots & & \vdots & & \vdots \\ d_c^{i1} & \cdots & d_c^{ij} & \cdots & d_c^{in} \\ \vdots & & \vdots & & \vdots \\ d_c^{n1} & \cdots & d_c^{nj} & \cdots & d_c^{nn} \end{bmatrix} \tag{1}$$

Step 2: Normalize the direct-influence matrix $\boldsymbol{D}$.

Matrix $\boldsymbol{D}$ is normalized using Eq. (2). The sum of rows or columns is now equal to one.

$$\boldsymbol{G} = \lambda \boldsymbol{D} \tag{2}$$

where $\lambda = \min_{i,j}\left\{ \frac{1}{\max_i \sum_{j=1}^{n} d_c^{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} d_c^{ij}} \right\}, \; i, j \in \{1, 2, \ldots, n\}$

Step 3: **Build a total-influential matrix** T_c

Once the normalized direct-influential matrix, $\boldsymbol{G}$, is obtained, the total-influential matrix, $\boldsymbol{T_G}$, can be obtained from Eq.(3), in which $\boldsymbol{I}$ denotes the identity matrix,

$$\begin{aligned} \boldsymbol{T_G} &= \boldsymbol{G}+\boldsymbol{G}^2+\boldsymbol{G}^3+\ldots+\boldsymbol{G}^\rho \\ &= \boldsymbol{G}(\boldsymbol{I}+\boldsymbol{G}+\boldsymbol{G}^2+\ldots+\boldsymbol{G}^{\rho-1})(\boldsymbol{I}-\boldsymbol{G})(\boldsymbol{I}-\boldsymbol{G})^{-1} \\ &= \boldsymbol{G}(\boldsymbol{I}-\boldsymbol{G}^\rho)(\boldsymbol{I}-\boldsymbol{G})^{-1} \\ &= \boldsymbol{G}(\boldsymbol{I}-\boldsymbol{G})^{-1}, \text{ when } \lim_{\rho\to\infty}\boldsymbol{G}^\rho=[0]_{n\times n} \end{aligned} \tag{3}$$

where $\boldsymbol{G}=\left[g_c^{ij}\right]_{n\times n}$, $0 \le g_c^{ij} < 1$, $0<\sum_{j=1}^n g_c^{ij} \le 1$ and $0<\sum_{i=1}^n g_c^{ij} \le 1$, and at least one row or column of the summation (but not all) equals one. In this way, $\lim_{\rho\to\infty}\boldsymbol{G}^\rho=[0]_{n\times n}$ is guaranteed. We denote the row and column sums of the total-influence matrix, $\boldsymbol{T}_c$, as column vectors $\boldsymbol{x}$ and $\boldsymbol{y}$ respectively: $\boldsymbol{T}_c=[t_c^{ij}]_{n\times n}$, $i,j\in\{1,2,\ldots,n\}$.

Step 4: **Analyze the results**.

At this stage, the row sums and the column sums of the matrix are separately expressed in vector form using Eqs. (4)-(5).

$$\boldsymbol{x}=\left[\sum_{j=1}^{n} t_c^{ij}\right]_{n\times 1}=\left[t_c^{i}\right]_{n\times 1}=(x_1,\ldots,x,\ldots,x_n)' \tag{4}$$

$$\boldsymbol{y}=\left[\sum_{i=1}^{n} t_c^{ij}\right]'_{1\times n}=\left[t_c^{j}\right]_{n\times 1}=(y_1,\ldots,y_j,\ldots,y_n)' \tag{5}$$

Let $i=j$ and $i,j\in\{1,2,\ldots,n\}$; the horizontal axis vector (x_i+y_i) is then defined by adding x_i to y_i, to illustrate the influence of the criterion. Similarly, the vertical axis vector (x_i-y_i) is defined by subtracting x_i from y_i, dividing the attribute into a causal cluster and an affected cluster.

In general, when (x_i-y_i) is positive, the criterion is part of the causal group, that is, criterion i affects other attributes. By contrast, if (x_i-y_i) is negative, the criterion is part of the affected group, that is, criterion i is influenced by other attributes. Mapping the data set (x_i+y_i, x_i-y_i) will lead to a graph called INRM. The graph provides valuable insight into how the preferred values in each dimension and criterion are interrelated to other criteria and how they can be improved.

2.2.2. DANP steps:

Step 1: Find the normalized matrix T_c^{nor} by dimensions and clusters.

Normalize $\boldsymbol{T}_C$ with the total degrees of effect and influence of the dimensions and clusters to obtain $\boldsymbol{T}_C^{nor}$ in Eq.(6).

$$\boldsymbol{T}_C^{nor} = \begin{array}{c c} & \begin{array}{ccccc} G_1 & \cdots & G_j & \cdots & G_m \\ c_{11}\ldots c_{1m_1} & \cdots & c_{j1}\ldots c_{jn_j} & \cdots & c_{m1}\ldots c_{mn_m} \end{array} \\ \begin{array}{c c} G_1 & \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots & \vdots \\ G_i & \begin{array}{c} c_{i1} \\ c_{i2} \\ \vdots \\ c_{in_i} \end{array} \\ \vdots & \vdots \\ G_m & \begin{array}{c} c_{m1} \\ c_{m2} \\ \vdots \\ c_{mn_m} \end{array} \end{array} & \begin{bmatrix} \boldsymbol{T}_c^{nor_{11}} & \ldots & \boldsymbol{T}_c^{nor_{1j}} & \ldots & \boldsymbol{T}_c^{nor_{1m}} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{nor_{i1}} & \ldots & \boldsymbol{T}_c^{nor_{ij}} & \ldots & \boldsymbol{T}_c^{nor_{im}} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{nor_{m1}} & \ldots & \boldsymbol{T}_c^{nor_{mj}} & \ldots & \boldsymbol{T}_c^{nor_{mm}} \end{bmatrix} \end{array} \tag{6}$$

Step 2: Build an unweighted super-matrix W_c.

The total-influential matrix is normalized into a super-matrix according to the inter-dependence between the relationships of the dimensions and criteria to obtain an unweighted super-matrix, $\boldsymbol{W}_C$, as shown in Eq.(7).

$$
\boldsymbol{W}_C = \left(\boldsymbol{T}_C^{nor}\right)' =
\begin{array}{cc}
 & \begin{array}{ccccc} G_1 & \cdots & G_j & \cdots & G_m \\ c_{11}\ldots c_{1m_1} & & c_{j1}\ldots c_{jn_j} & & c_{m1}\ldots c_{mn_m} \end{array} \\
\begin{array}{c} G_1 \begin{array}{c} c_{11} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots \\ G_i \begin{array}{c} c_{i1} \\ \vdots \\ c_{in_i} \end{array} \\ \vdots \\ G_m \begin{array}{c} c_{m1} \\ \vdots \\ c_{mn_m} \end{array} \end{array} &
\begin{bmatrix}
\boldsymbol{W}^{11} & \cdots & \boldsymbol{W}^{i1} & \cdots & \boldsymbol{W}^{m1} \\
\vdots & & \vdots & & \vdots \\
\boldsymbol{W}^{1j} & \cdots & \boldsymbol{W}^{ij} & \cdots & \boldsymbol{W}^{mj} \\
\vdots & & \vdots & & \vdots \\
\boldsymbol{W}^{1m} & \cdots & \boldsymbol{W}^{im} & \cdots & \boldsymbol{W}^{mm}
\end{bmatrix}
\end{array}
\tag{7}
$$

Unweighted super-matrix W_C is the transposed form of $\boldsymbol{T}_C^{nor}$. If a blank or 0 appears in the matrix, it means that the two dimensions or attributes are independent.

Step 3: Find the normalized total-influential matrix of dimension $\boldsymbol{T}_G^{nor}$.

The total-influential matrix, $\boldsymbol{T}_G$, needs to be normalized by dividing it by the following sum: $t_G^i = \sum_{j=1}^{m} t_G^{ij}$

$$
\boldsymbol{T}_G = \begin{bmatrix}
t_G^{11} & \cdots & t_G^{1j} & \cdots & t_G^{1m} \\
\vdots & & \vdots & & \vdots \\
t_G^{i1} & \cdots & t_G^{ij} & \cdots & t_G^{im} \\
\vdots & & \vdots & & \vdots \\
t_G^{m1} & \cdots & t_G^{mj} & \cdots & t_G^{mm}
\end{bmatrix}
\begin{array}{l}
\rightarrow \sum_{j=1}^{m} t_G^{1j} = t_G^1 \\
\\
\rightarrow \sum_{j=1}^{m} t_G^{ij} = t_G^i \\
\\
\rightarrow \sum_{j=1}^{m} t_G^{mj} = t_G^m
\end{array}
\tag{8}
$$

The normalized matrix is presented as $\boldsymbol{T}_G^{nor}$. Define the sum of each row as $t_G^i = \sum_{j=1}^{m} t_G^{ij}$, where $i = 1, \ldots, m$. $\boldsymbol{T}_G$ can be normalized by dividing the elements in each row by the row sum as in Eq. (8). We will, then, have the total-influential matrix, $\boldsymbol{T}_G$, which can be normalized and presented as $\boldsymbol{T}_G^{nor} = \left[t_G^{ij} / t_G^i\right]_{m \times m}$ (see Eq. (9)). Each row of $\boldsymbol{T}_G^{nor}$ sums to one, so that $\sum_{j=1}^{m} t_G^{nor_{ij}} = 1$.

$$
\boldsymbol{T}_G^{nor} = \begin{bmatrix}
t_G^{11}/t_G^1 & \cdots & t_G^{1j}/t_G^1 & \cdots & t_G^{1m}/t_G^1 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
t_G^{i1}/t_G^i & \cdots & t_G^{ij}/t_G^i & \cdots & t_G^{im}/t_G^i \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
t_G^{m1}/t_G^m & \cdots & t_G^{mj}/t_G^m & \cdots & t_G^{mm}/t_G^m
\end{bmatrix}
= \begin{bmatrix}
t_G^{nor_{11}} & \cdots & t_G^{nor_{1j}} & \cdots & t_G^{nor_{1m}} \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
t_G^{nor_{i1}} & \cdots & t_G^{nor_{ij}} & \cdots & t_G^{nor_{im}} \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
t_G^{nor_{m1}} & \cdots & t_G^{nor_{mj}} & \cdots & t_G^{nor_{mm}}
\end{bmatrix}
\tag{9}
$$

Step 4: Find the influential weights of the D-DANP.

The total-influential matrix, $\boldsymbol{T}_C$, needs to be normalized by dividing the dimension and cluster by the row sums (as in Eq. (9)), $\boldsymbol{T}_C$ which will lead to $\boldsymbol{T}_C^{nor}$. An unweighted super-matrix $\boldsymbol{W}_C$ can be obtained by transposing $\boldsymbol{T}_C^{nor}$, that is, $\boldsymbol{W}_C = \left(\boldsymbol{T}_C^{nor}\right)'$. A weighted super-matrix $\boldsymbol{W}_C$ can be obtained by the product of $\boldsymbol{T}_G^{nor}$ and $\boldsymbol{W}_C$, that is, $\boldsymbol{W} = \boldsymbol{T}_G^{nor} \boldsymbol{W}_C$ (Eq. (10)). This matrix improves the traditional ANP by using equal weights to make it appropriate for the real world. This result demonstrates that the values for influence levels are the basis of normalization to determine a weighted super-matrix.

$$W = T_G^{nor} W_C = \begin{bmatrix} t_G^{nor_{11}} W_C{}^{11} & \cdots & t_G^{nor_{i1}} W_C{}^{i1} & \cdots & t_G^{nor_{m1}} W_C{}^{m1} \\ \vdots & & \cdots & & \vdots \\ t_G^{nor_{1j}} W_C{}^{1j} & \cdots & t_G^{nor_{ij}} W_C{}^{ij} & \cdots & t_G^{nor_{mj}} W_C{}^{mj} \\ \vdots & & \vdots & & \vdots \\ t_G^{nor_{1m}} W_C{}^{1m} & \cdots & t_G^{nor_{im}} W_C{}^{im} & \cdots & t_G^{nor_{mm}} W_C{}^{mm} \end{bmatrix} \quad (10)$$

Step 5: Obtain the D-DANP influence weights.

Limit the weighted super-matrix by raising it to a sufficiently large power ρ until it converges and becomes a stable super-matrix. This matrix is the set of global priority vectors which define the influential weightings $\boldsymbol{w}^* = (w_1^*, ..., w_j^*, ..., w_n^*)$ from $\lim_{\rho\to\infty}(\boldsymbol{W})^{\rho}$ for the attribute. Thus, IWs of each criterion in every dimension, the local weights of dimension $\boldsymbol{w}_G$ is obtained by the local weights. Then, the global weights of each criterion is divided by the local weights of its own dimension to yield the local weights of criteria $\boldsymbol{w}_C$ .Finally, the DEMATEL-based analytic network technique (D-DANP) is applied.

2.3. DANP

This stage produces the weights (IWs) of the attributes for the developed matrices of INRM in the previous stage, using the DEMATEL-based analytic network process (DANP) to find the IWs of the attributes. This stage has five steps, described in the appendix in detail. Finally, this stage gives the IWs.

2.4. Modified VIKOR (MV)

This stage offers the final measures of evaluated performance of the modes and tributes, using modified VIKOR. The VIKOR approach is a compromise ranking list methodology. The method could be implemented within the Multiple Attribute Decision-Making model so that the preferred stability of the compromise solution can be achieved from the initial weights available from D-DANP.

VIKOR introduces a multiple attribute ranking index based on a particular measure of "closeness" to the "ideal" solution. The criterion that is the closest to the ideal point based on the measure is regarded as the highest performance score among all alternatives (the larger, the better). Let f_{ij} be these scores, then $f_j^* = \max\{f_{kj} \mid k = 1, 2, ..., K\}$. Likewise, the negative ideal point is set as the lowest performance score among all alternatives, that is, $f_j^- = \min\{f_{kj} \mid k = 1, 2, ..., K\}$.

The traditional "max–min" approach would result in choosing the best among inferior alternatives, meaning "picking the relatively good apple among a barrel of rotten apples". To avoid this situation, we propose a modified VIKOR (MV) as follows. Let the alternatives be denoted as $A_1, ..., A_k, ..., A_K$. $\boldsymbol{w}_j^*$ is set to the weight of the j_{th} attribute, where j=1, 2, …, n , and r_i is the number of attributes. We especially use the relative influential weightings of the attribute j from the D-DANP to make it applicable to the real-world situation j=1, 2, …, n and r_i. We then normalize the ranking performance scores so that the scale starts from 0 (the worst value, $f_j^{worst} = 0$) to 10 (the best value, called the aspiration level, $f_j^{aspired} = 10$), and the scores of the j_{th} attribute are denoted by $\boldsymbol{f}_{kj}$ for an alternative $\boldsymbol{A}_k$ with gap r_{kj}. The development of the MV method begins with forming the gaps as

$$r_{kj} = \left\{(|\, f_j^{aspired} - f_{kj}\,|) / (|\, f_j^{aspired} - f_j^{worst}\,|) \middle| k = 1, 2, ..., K;\ j = 1, 2, ..., n\right\} \quad (11)$$

where $f_j^{aspired}$ is the aspiration level (taking the highest score of 10) and f_j^{worst} is the one with the value of 0 for attribute j , $j = 1, 2, ..., n$.

The aspiration level defined as such is different from the traditional approach $f_j^{aspired} \max_k f_{kj}$. It is more appropriate for the analysis of technology transfer and impediments to it in the real world. To ensure that the normalized scale of the gap, r_{kj}, can be reduced to zero when the best value is set with no gap, we set the normalized scale of the gap r_{kj} to one. The worst value will have the largest gap. A priority improvement strategy can then be established by determining the gaps for each attribute r_{kj} for each dimension (i.e., each participant in this study) as $r_{kj}^{M_i} = \sum_{j=1}^{n_i} w_j^{M_i} r_{kj}^{M_i}$. The alternatives can be calculated by $R_k = \sum_{j=1}^{n} w_j r_{kj}$, where w_j is the IWs calculated by the D-DANP. Approaching and achieving the aspiration level requires a zero gap.

In the end, the proposed HMADM model formed the D-DANP-MV gives an overall picture of attributes in each participant by first using the DEMATEL technique to construct the INRM and then by focusing on the influential weights of the DANP computed from the D-DANP. In the final stage, it applies the MV to evaluate the performance gaps and single out the way forward to achieving the aspiration level of the alternatives. Figure 2 illustrates the HMADM in a diagram.

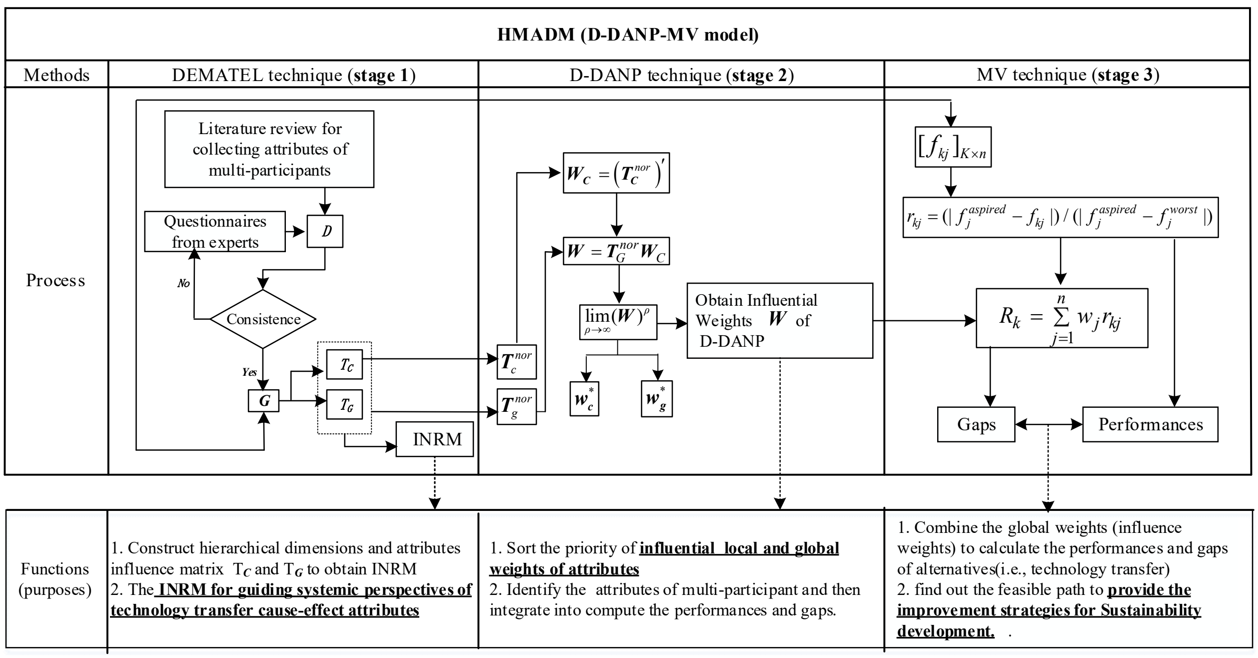

Fig. 2. Main functions and stages of the HMADM model

3. Empirical case

3.1. *Case description*

Since 2019, Shaanxi Provincial Science and Technology Resources Coordination Center has considered the dispersed foundational resources and traditional offline service models are no longer sufficient to meet the demands for efficiency, quality, accuracy, and immediacy of new technologies matching services in the context of information overload. There is an urgent need to elevate services from information to knowledge. this project aimed involved the mechanization of technology consulting into a knowledge-based service driven. Specifically, the research focuses on understanding the rules and principles governing the diverse entities, multiple data sources, and hierarchical knowledge structures that interact in the transition from information services to knowledge services about the technology transfer. Therefore, this platform, named “Technology Consulting and Service Platform” is centered in the new technologies round five industries and twenty cutting-edge fields including agriculture of IOT, intelligent manufacturing, new materials, energy, and science and technology finance.

With the goal of "resource collaborative management," this platform establishes a new economic and technical consulting database, creates consulting service tools based on big data, and develops professional consulting services that integrate to facilitate the real technical needs of buyers and sellers. The success rate of technology transfer matching the seller's is a major issue.

3.2. Data collecttion

This study collected data by selecting the related attributes for improving the technology transfer process among universities/research institutes, corporations, and intermediary agencies considered in internal-external relationships. The selection uses the D-DANP model, including the DEMETEL technique (to construct the hierarchical interrelationship model and build the INRM) and the DANP method (to find out the IWs using the DEMATEL for attributes with interdependence). Table 1 represents these influential attributes. According to Table 1, there are three participants: universities/research institutes (***P_1***), corporations (***P_2***), and intermediary agencies service (***P_3***). Together, 12 attributes describe technology transfer among these participants.

This research engages 50 experts with many years of technology transfer-related experience. Among them, 21 experts are from the related industries as mentioned above and 20 experts are from universities who respond to the research questionnaire, covering 12 attributes and 3 types of participants described in Table 1. The questionnaire uses a five-point scale ranging from 0 (absolutely no influence) to 4 (very high influence) to determine the degree of influence each attribute from each participant has on others. We then survey 10 different experts via personal interviews or by asking them to fill out the questionnaire and collect the responses. Each interview (face-to-face) plus writing the questionnaire took about 30-40 minutes.

This data is gathered to evaluate the performance of the main three modes of technology transfer, defined as follows.

1) Autonomous technology entrepreneurship involves starting new businesses that utilize advanced technologies and are independent of universities, research institutions, or corporations.

2) Technology licensing is the legal process of allowing the use, development, or commercialization of technology, usually in exchange for compensation, such as royalties or fees.

3) Technology shareholding refers to owning shares in a company that uses or develops technology, allowing investors to share in profits and growth while supporting innovation.

Table 1. Description of participants and their technology transfer attributes

Participants/Attributes	Explanation
Universities/research institutes (P_1)	Education and research centers
Technology readiness (c_1)	Distance from technology to product
Technology embeddedness (c_2)	Difficulty and complexity of technology transfer
Researcher participation (c_3)	Involvement of researchers in the subsequent transformation activities
Institutional arrangements (c_4)	Researcher's professional title appraisal system, performance appraisal system, transformation incentive policy, benefit distribution
Corporations (P_2)	Legal entities focused on generating profit through business operations
Demand for new technology (c_5)	New technologies to its operations
Relationship with technology supplier (c_6)	Strategic relationship with supplier or independent provider
Learning ability (c_7)	Efficiency in adopting and mastering new technologies
Management ability (c_8)	Including technical management, resource allocation, organizational management experience, and operational capacity

Intermediary agencies service (P₃)	agencies facilitating interactions and transactions between parties like individuals, businesses, or government entities
Assessment ability (c_9)	Capacity to accurately evaluate the value of technology
Communication ability (c_{10})	Providing a trading information platform and assisting both parties to connect and negotiate
Technical collaboration ability (c_{11})	Fundraising; Implementation of site, equipment, and supporting activities; Supporting recruitment and training of all kinds of personnel; Other auxiliary and supporting work
Operational assistance ability (c_{12})	New product appraisal and quality certification; Formulation and implementation of plans for business development; Technical stability and improvement, equipment maintenance and accessories implementation: technical training of staff; Establishment of a management system

3.3. Obtaining IWs by combining DEMATEL and DANP into D-DANP

This empirical study measures and ranks the effects of technology transfer groups on the technology transfer modes using the influential attributes in a comparative analysis. Figure 3 displays the diagram of the empirical case in this study. According to Figure 3, the DEMATEL technique gathers responses to compute the influence relationship matrix of the three participants, $\boldsymbol{T}_G$ (Table 2), and 12 attributes, $\boldsymbol{T}_C$ (Table 3), using Eqs. (3) and (8). Then, Eqs. (4) and (5) investigate the cause-effect direction of the attributes, showing which attributes have the most influence compared with the others. Table 4 represents the results and the INRM of the DEMATEL technique from the cause-effect analysis. Having determined the relationship structure of technology transfer attributes, the DANP method obtains the influential weights of the attributes. This approach compares the strength of the relationship between any two attributes based on the INRM. To this end, transposing the normalized matrix $\boldsymbol{T}_C^{nor}$ gives an unweighted super-matrix $\boldsymbol{W}_C$, that is, $\boldsymbol{W}_C = (\boldsymbol{T}_C^{nor})'$. Then, Eqs. (6) – (10) get the influential weights $\boldsymbol{W}^* = \boldsymbol{T}_G^{nor}\boldsymbol{W}_C$ of DANP. Table 5 shows the influential weights of DANP computed by raising the weighted super-matrix $\lim_{\rho\to\infty}(\boldsymbol{W})^{\rho}$ to a high power until it reaches a steady-state.

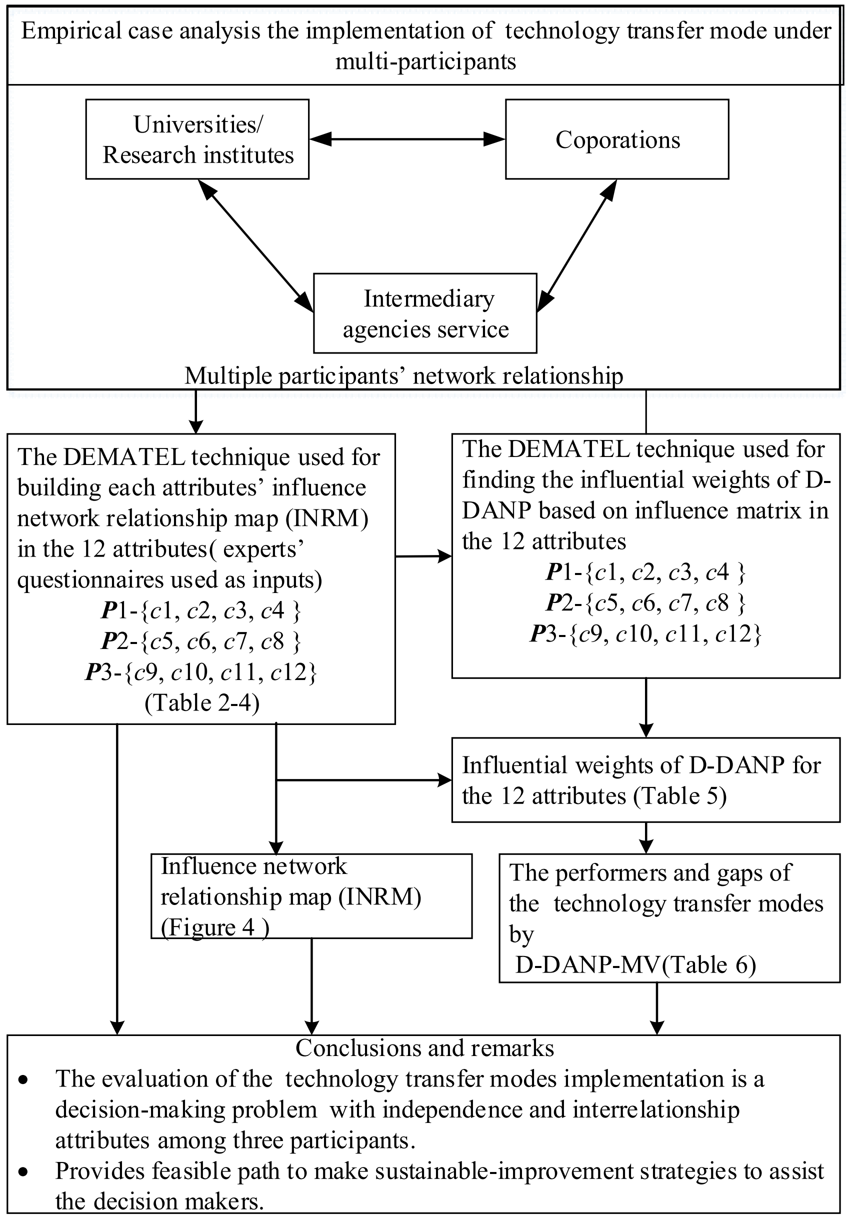

Fig. 3. Diagram of the empirical case

Table 2 represents the total effects of attributes on the 3 groups of participants. According to Table 2, the attributes have the greatest cause-and-effect interrelationships with universities and research institutes whose influencing and influenced degrees are 1.202 and 1.053, respectively. This result implicitly shows the considerably effective role of universities and research institutes in technology transfer. In addition, Table 3 presents the network relationship map of attributes. Regarding Table 3, technology readiness, technology embeddedness, and researcher participation (c_1, c_2, and c_3) show the greatest influencing values, 4.900, 5.165, and 4.849, and influenced values, 3.900, 4.449, and 4.789, respectively. This result implies the substantial impact of technology readiness, technology embeddedness, and researcher participation as three main attributes in the network relationship map.

Table 2. Map of network relationships of attributes

T_G	P_1	P_2	P_3	x_i (influencing)
Universities/research institutes	0.393	0.403	0.406	**1.202**
Corporations	0.353	0.339	0.347	**1.039**
Intermediary agencies	0.307	0.308	0.313	**0.928**
y_i (influenced)	**1.053**	**1.05**	**1.066**	

Table 3. Disaggregated influential attributes of the participants

T_c	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	x_i
c_1	0.311	0.459	0.482	0.356	0.397	0.435	0.424	0.368	0.427	0.432	0.444	0.365	**4.900**
c_2	0.418	0.374	0.506	0.387	0.416	0.465	0.450	0.393	0.438	0.461	0.468	0.390	**5.165**
c_3	0.389	0.447	0.379	0.376	0.392	0.459	0.431	0.369	0.391	0.430	0.432	0.354	**4.849**
c_4	0.331	0.385	0.429	0.260	0.340	0.402	0.365	0.338	0.347	0.394	0.391	0.337	**4.319**
c_5	0.359	0.404	0.429	0.339	0.293	0.423	0.396	0.347	0.373	0.402	0.401	0.337	**4.502**
c_6	0.341	0.389	0.437	0.319	0.358	0.325	0.387	0.347	0.346	0.387	0.373	0.323	**4.331**
c_7	0.319	0.368	0.411	0.293	0.341	0.381	0.288	0.323	0.326	0.352	0.362	0.307	**4.070**
c_8	0.285	0.326	0.349	0.281	0.304	0.344	0.338	0.232	0.299	0.334	0.336	0.294	**3.720**
c_9	0.266	0.299	0.318	0.258	0.276	0.317	0.290	0.263	0.233	0.330	0.334	0.293	**3.476**
c_{10}	0.292	0.327	0.360	0.280	0.293	0.371	0.330	0.297	0.328	0.281	0.366	0.326	**3.852**
c_{11}	0.311	0.361	0.363	0.291	0.304	0.359	0.339	0.295	0.330	0.366	0.289	0.323	**3.930**
c_{12}	0.278	0.309	0.326	0.269	0.286	0.330	0.300	0.278	0.303	0.337	0.336	0.226	**3.577**
y_i	**3.900**	**4.449**	**4.789**	**3.709**	**4.001**	**4.610**	**4.336**	**3.849**	**4.140**	**4.505**	**4.532**	**3.874**	

Note 1: $1/n^2\sum_{i=1}^{n}\sum_{j=1}^{n}(\frac{\left|t_{ij}^{\xi}-t_{ij}^{\xi-1}\right|}{t_{ij}^{\xi}})\times 100\% = 3.76\% < 5\%$ the significant level is 96.24%, where ξ denotes the number of experts and t_{ij}^{ξ} is the average of *i* attribute on *j*; and n indicates attribute. In our example $n=12$ and the matrix is $n\times n$.

Note 2: Technology readiness (c_1), Technology embeddedness (c_2). Researcher participation (c_3), Institutional arrangements (c_4), Demand for new technology (c_5), Relationship with technology supplier (c_6), Learning ability (c_7), Management ability (c_8), Assessment ability (c_9), Communication ability (c_{10}), Technical collaboration ability(c_{11}), and Operational assistance ability(c_{12})

Figure 4 demonstrates the resulted interrelationships among groups of participants, the importance of attributes for each group, and the cause-effect direction of attributes. Based on Figure 4, universities/research institutes (P_1) play an important role in systemic view of technology transfer and have a strong influence on the other two groups of participants P_1, P_2 and P_3, consistent with the results in Table 2.

Table 4 confirms the greatest causal effects of technology readiness and universities/research institutions. With regard to Table 4, only universities/research institutes (P_1) have a positive value, 0.149, implying the degree of its causal effect. This result shows that only universities/research institutes have a causal effect and their influence is directed at corporations and intermediary agencies. Moreover, only five attributes show positive causality values, implying their considerable causal effects. Among them, the strongest causal attribute, 1.001, goes to technology readiness **(**c_1**),** which receives the highest score P_2. The next strongest attributes are technology embeddedness **(**c_2**)**, 0.716, researchers' participation **(**c_3**)**, 0.060, institutional arrangements **(**c_4**)**, 0.610, and demand for new technology **(**c_5), 0.501. These findings confirm the results in Table 3.

The last one, the demand for new technology **(**c_5), is associated with corporations (P_2). Despite a causal attribute, it is exposed to the influence of other attributes. We manage to visualize this interrelation of the attributes through the application of DEMTEL and the construction of the INRM. The visualization assists decision-makers to identify the main attributes and their causality more easily and take steps to fortify the effective and affected attributes through the causal link.

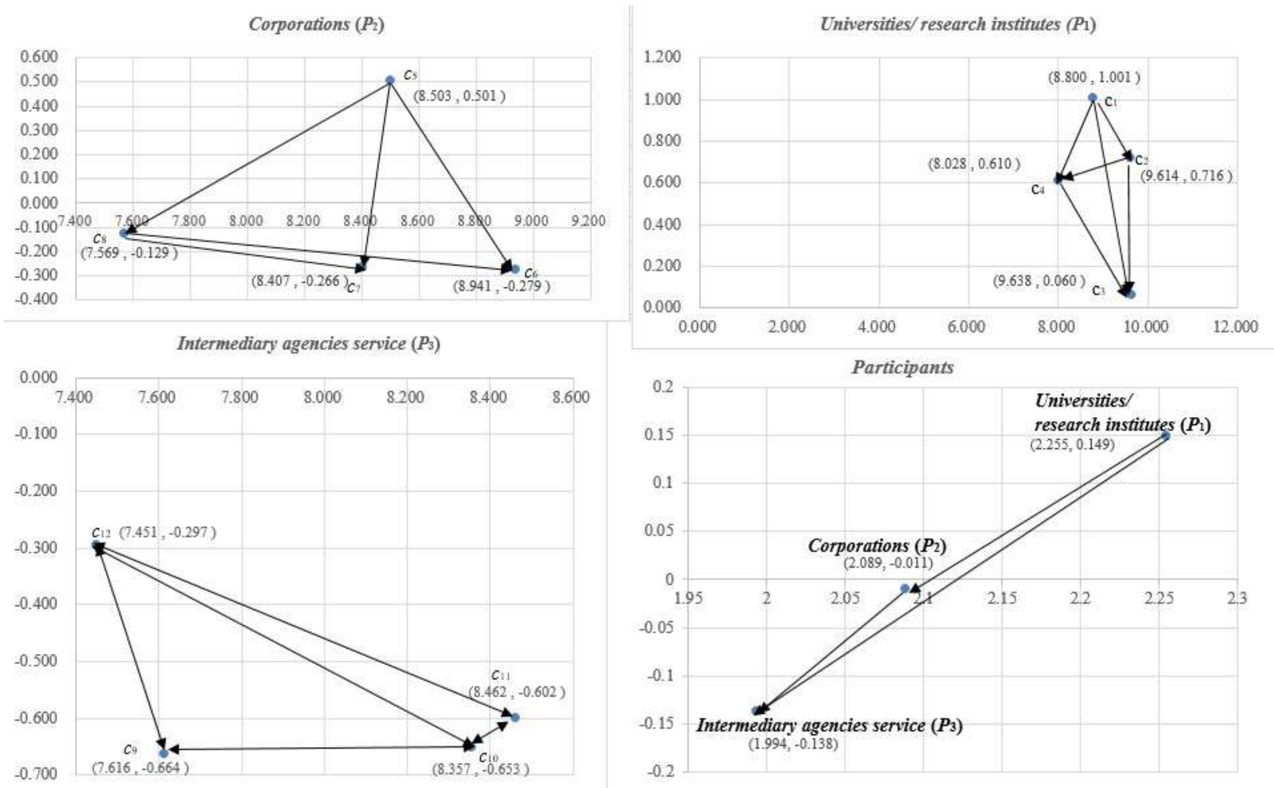

Fig. 4. INRM of hierarchical levels of participants and attributes

Table 4. Cause-effect analysis of participants and attributes

Participants/ attributes		x_i (influencing)	y_i (influenced)	$x_i + y_i$ (centrality)	$x_i - y_i$ (causality)	Cause/ Effect
$\boldsymbol{P}_1$	Universities/research institutes	1.202	1.053	2.255	0.149	Cause
c1	Technology readiness	4.900	4.900	8.800	1.001	Cause
c2	Technology embeddedness	5.165	5.165	9.614	0.716	Cause
c3	Researcher participation	4.849	4.849	9.638	0.060	Cause
c4	Institutional arrangements	4.319	4.319	8.028	0.610	Cause
$\boldsymbol{P}_2$	Corporations	1.039	1.05	2.089	-0.011	Effect
c5	Demand for new technology	4.502	4.502	8.503	0.501	Cause
c6	Relationship with technology supplier	4.331	4.331	8.941	-0.279	Effect
c7	Learning ability	4.070	4.070	8.407	-0.266	Effect
c8	Management ability	3.720	3.720	7.569	-0.129	Effect
$\boldsymbol{P}_3$	Intermediary agencies	0.928	1.066	1.994	-0.138	Effect
c9	Assessment ability	3.476	3.476	7.616	-0.664	Effect
c10	Communication ability	3.852	3.852	8.357	-0.653	Effect
c11	Technical collaboration ability	3.930	3.930	8.462	-0.602	Effect
c12	Operational assistance ability	3.577	3.577	7.451	-0.297	Effect

After DEMATEL output, the second stage uses DANP to explore the ways to interfere and address problems and to form the weighting matrix. Put together, these two stages constitute our D-DANP approach.

Table 5 presents these weights. The D-DANP sorts out the priority areas for continued improvement of technology transfer. According to Table 5, the top attribute for improving technology transfer is researcher participation (c_3) with an influence weight of 0.094, followed by learning ability (c_6) with 0.091, communication ability (c_{10}) with 0.89, technical collaboration ability (c_{11}) with 0.089, and technology embeddedness (c_2) with 0.088. Figure 4 shows a more systemic perspective (at the participant or attribute level). The visual aspect, in particular, makes it easy for decision-makers to evaluate attributes and decide the most important one, worthy of attention, to facilitate technology transfer.

Table 5. Influential weights by D-DANP ranking

D-DANP	Attribute	Influence weight	Ranking
c_3	Researcher participation	0.094	1
c_6	Learning ability	0.091	2
c_{10}	Communication ability	0.089	3
c_{11}	Technical collaboration ability	0.089	3
c_2	Technology embeddedness	0.088	5
c_7	Management ability	0.085	6
c_9	Assessment ability	0.081	7
c_5	Relationship with technology supplier	0.079	8
c_1	Technology readiness	0.077	9
c_{12}	Operational assistance ability	0.077	9
c_8	Assessment ability	0.076	10
c_4	Institutional arrangements	0.073	11

3.4. Performance evaluation and gaps in technology transfer modes by MV

The questions asked in the survey provide natural language descriptions with scores ranging from 0 (worst level) to 10 (aspiration level). These responses provide a reference for the comparison of the three technology transfer modes based on their performance and gaps. These three modes are autonomous technology entrepreneurship, technology licensing, and technology shareholding, shown by modes 1, 2, and 3, respectively. The responses are from 15 experts in total: 7 experts with university/research institute ($\boldsymbol{P}_1$) association, 4 experts with corporate ($\boldsymbol{P}_2$) association in the manufacturing industry, and 4 experts with intermediary agencies ($\boldsymbol{P}_3$) association.

Table 6 represents the efficacy of these three technology transfer modes, by computing the gap values through the MV method, and the co-influences found through D-DANP (the third stage in D-DANP-MV). Table 6 shows that, in terms of cooperation, technology licensing (mode 2) attains the highest score of 5.456 and outperforms the other modes. However, based on the total gap value, autonomous technology entrepreneurship (mode 1) (with a gap value of 0.341) has a lower gap than those of technology licensing (mode 2) (gap value 0.421) and technology shareholding (mode 3) (gap value 0.413). The calculated gaps represent the distance between an attribute's actual performance and its aspiration level. The total gap value represents the sum of gaps for all attributes obtained from the local weight and gap for each attribute.

Table 6. Comparing the performance of technology transfer modes using MV

Participants/ attributes	influence weights		mode 1		mode 2		mode 3	
	Local weights	Global weight	Perfor-mance	Gap	Perfor-mance	Gap	Perfor-mance	Gap
$\boldsymbol{P_1}$	**0.332**		**7.712**	**2.560**	**6.523**	**2.166**	**6.607**	**2.194**
c_1	0.232	0.077	7.812	0.603	8.719	0.673	7.366	0.568
c_2	0.264	0.088	6.387	0.493	7.345	0.567	7.995	0.617
c_3	0.283	0.094	7.517	0.580	5.729	0.442	5.875	0.453
c_4	0.220	0.073	6.971	0.538	4.298	0.332	5.192	0.400
$\boldsymbol{P_2}$	**0.331**		**4.086**	**1.352**	**5.538**	**1.781**	**5.495**	**1.819**
c_5	0.238	0.079	3.719	0.287	5.391	0.416	4.963	0.383
c_6	0.275	0.091	3.870	0.298	5.464	0.421	6.605	0.509
c_7	0.258	0.085	4.041	0.312	5.437	0.419	5.537	0.427
c_8	0.229	0.076	4.714	0.364	5.228	0.403	4.874	0.376
$\boldsymbol{P_3}$	**0.3306**		**3.066**	**1.030**	**5.783**	**1.943**	**5.247**	**1.763**
c_9	0.244	0.081	2.914	0.225	6.491	0.501	6.449	0.497
c_{10}	0.266	0.089	2.902	0.224	5.930	0.457	5.490	0.423
c_{11}	0.268	0.089	3.110	0.240	5.856	0.452	4.963	0.383
c_{12}	0.230	0.077	3.340	0.258	4.854	0.374	4.084	0.315
Total Performance			**4.419**		**5.456**		**5.352**	
Total Gap				**0.341**		**0.421**		**0.413**

Note 1: universities/research institutes ($\boldsymbol{P_1}$), corporations ($\boldsymbol{P_2}$), intermediary agencies ($\boldsymbol{P_3}$); technology readiness (c_1), Technology embeddedness (c_2). Researcher participation (c_3), Institutional arrangements (c_4), Demand for new technology (c_5), Relationship with technology supplier (c_6), Learning ability (c_7), Management ability (c_8), Assessment ability (c_9), Communication ability (c_{10}), Technical collaboration ability(c_{11}), Operational assistance ability(c_{12}), autonomous technology entrepreneurship (mode 1), technology licensing (mode 2), technology shareholding (mode 3).
Note 2: The total gap value is calculated by $R_k = \sum_{j=1}^{n} w_j r_{kj}$.

Using the aspiration level (10) as the benchmark helps to identify areas that need improvement. These areas need to be improved to achieve the overall goal of sustainability. As per results, resources need to be integrated and effort must be put into selecting the technology transfer mode that better aligns with the goals of each participant.

At the attribute level, all three modes perform poorly. The poor performance is more noticeable for certain attributes. There are also larger gaps in mode 1. Some of these gaps relate to the diversification of technology readiness (c_1) (gap value of 0.603), management ability (c_8) (gap value of 0.364), and operational assistance ability (c_{12}) (gap value of 0.258). In mode 2, the major gaps are related to the diversification of technology readiness (c_1) (gap value 0.673), relationship with technology supplier (c_6) (gap value 0.421), and assessment ability (c_9) (gap value 0.501). Finally, mode 3 has major gaps in the diversification of technology readiness (c_1) (gap value 0.568) and relationship with technology supplier (c_6) (gap value 0.509), and assessment ability (c_9) (gap value 0.497). Common to all of these, technology readiness (c_1) is the main attribute that affects all participants regardless of their type and is important to the synergy, capabilities, and the accruing benefits, whether those capabilities are at the macro level (i.e., participants), micro level (i.e., attribute).

3.5. Discussion

The findings of this research analyze the impact of various modes on technology transfer at both macro and micro levels. According to these findings, universities and research institutions have the strongest impact on technology transfer at the macro level, and technology licensing is the most feasible mode for the micro level of technology transfer.

At the macro level, technology transfer as a whole receives an overall positive effect from all the studied modes, specifically universities/research institutions. According to the findings, all the studied modes can wholly improve technology transfer. Among these modes, universities/research institutions show the greatest cause-and-effect interrelationships with all the attributes, especially directed at corporations and intermediary agencies. This finding mainly implies that universities/research institutions have the strongest causal effects on the other two modes in the technology transfer ecosystem. For this reason, an effective technology transfer should put emphasis and resources into the universities/research institutes and have a focus on attributes such as technology readiness, technology embeddedness, researcher participation, and institutional arrangements.

At the micro level, the findings show that technology licensing has not only the highest performance but also the largest gap. According to this finding, technology licensing is the most feasible way to cater to technology transfer at the macro level from the micro level. Technology transfer takes the greatest effect from universities/research institutes via technology licensing. Thus, researcher participation plays a crucial role in reducing not only the gap in technology licensing but also the total gap.

Moreover, the findings imply that, after improving researcher participation in universities/research institutes, the spillover effects of communication and technical collaboration within intermediary agencies play a vital role in technology transfer. According to the findings, the most effective attributes for improving technology transfer are researcher participation, learning ability, communication, and technical collaboration. This finding highlights not only the importance of university, research, and learning, but also the spillover effects of communication and collaboration. This conclusion is consistent with the concept of "spillover effects" of the integrated sustainability perspective proposed.

Table 7 represents the priority of improvement strategies in the macro and micro levels, according to the mentioned findings and with regard to Tables 5 and 6. Based on Table 7, improving the learning ability of corporations would make the overall technology transfer the most effective in a multi-participant environment. In top level, promoting the universities/research institutes is the most effective strategy to improve technology transfer ecosystem since it has the greatest impact on technology licensing mode in the technology transfer. In bottom level, reducing the total gap requires focusing on some attributes including technology embeddedness (c_2) and researcher participation (c_3). Thus, a multilevel and continuous improvement is necessary to improve the process of technology licensing and make technology transfer more effective. This improvement involves reducing gaps and addressing performance issues, particularly in terms of technology licensing compared with the other two modes of technology transfer. Additionally, considering the co-influence among multiple attributes and initiating improvement strategies can help advance spillover effects in technology transfer.

Table 7. Technology transfer implement improvement by HMADM model

Multi-level interactive relationship of participants	Strategies (Priority of improvement targets by cause attributes)
Macro-level	$\boldsymbol{P}_1$□ $\boldsymbol{P}_2$□$\boldsymbol{P}_3$
Micro-level	$\boldsymbol{P}_1$: (c_3)_(c_2)□ $\boldsymbol{P}_2$: (c_6)□$\boldsymbol{P}_3$: (c_{10})_ (c_{11})

Note: universities/research institutes ($\boldsymbol{P}_1$), corporations ($\boldsymbol{P}_2$), intermediary agencies ($\boldsymbol{P}_3$); Technology embeddedness (c_2), Researcher participation (c_3), Relationship with technology supplier (c_6), Communication ability (c_{10}), and Technical collaboration ability (c_{11}).

4. Conclusions and remarks

Technology transfer plays an important role in linking academia and industries together in the interest of better and more practical innovations. However, impediments are hindering the move from theory to practice that are difficult to perceive without proper analysis. Various attributes and different types of participants make understanding the mechanics of a technology transfer process too complicated without proper tools.

This study uses a literature review and expert's opinion to construct a systemic perspective of technology transfer as a hierarchical network where participants are at the upper level and attributes are at the lower level. Then, the DEMATEL investigates the interrelationship between all these factors in driving a technology transfer process.

The outcomes of this investigation suggest that universities and research institutes exert a significant influence on the other participants involved in a technology transfer ecosystem, making them a critical factor in an effective technology transfer strategy. Therefore, it is important to prioritize and allocate resources toward these institutions, with emphasis on the attribute of researcher participation. Additionally, the study reveals that improving communication and technical collaboration abilities within intermediary agencies, after enhancing researcher participation in universities and research institutes, can further enhance the effectiveness of the technology transfer ecosystem. Moreover, the research identifies technology licensing as the technology transfer mode with the largest gap compared to other modes, indicating ample room for improvement in this area.

Methodologically, the proposed model is an innovation of the study which can be used to adjust the influential weights of attributes based on the industry or field, and can guide the selection of technology transfer modes for a specific industry while identifying and minimizing gaps in the technology transfer process.

This paper presents theoretical, practical, and policy implications for sustainable development in the world and China, related to the development of an INRM framework for technology transfer ecosystems.

From the global perspective, the framework emphasizes the role of universities/research institutes as the main cause factor influencing technology transfer effectiveness and identifies influential attributes such as technology readiness, researcher participation, institutional arrangements, and technical collaboration ability. Practical implications include improving researcher participation, enhancing communication and technical collaboration ability, and improving the learning ability of corporations. Policy implications suggest prioritizing the development of universities/research institutes and improving the communication and technical collaboration ability of intermediary agencies. The proposed model can be customized to achieve better outcomes and sounder decisions in technology transfer.

From the viewpoint of development in China, this country is a rapidly growing economy with a strong emphasis on innovation and technology transfer. The proposed INRM framework is a valuable tool that can assist Chinese policymakers and industry leaders in improving technology transfer processes. China has invested extensively in building a robust research and development infrastructure, making the framework's focus on universities and research institutes particularly relevant.

Furthermore, the findings suggest that research participation is crucial for successful technology transfer, and policymakers and industry leaders should prioritize encouraging and supporting researchers, specifically in China. Additionally, intermediary agencies play a crucial role in facilitating technology transfer, and policymakers and industry leaders should focus on improving these agencies' communication and technical collaboration abilities to enhance technology transfer outcomes.

The policy implications of this paper, specifically for China, are two-fold. Firstly, policymakers should prioritize developing universities and research institutes to strengthen the research and development infrastructure, creating a more conducive environment for technology transfer. Secondly, policymakers should focus on improving intermediary agencies' communication and technical collaboration abilities to facilitate technology transfer between universities, research institutes, and corporations. The paper also emphasizes the importance of technology licensing, which policymakers should consider when formulating policies to promote technology transfer in the country.

Given that experts interviewed in this study put more emphasis on researcher participation, the choice of technology transfer mode and the proposed plan to improve a particular technology transfer mode can also be influenced by this observation. The gaps we compute for each mode guide how this improvement can be achieved and how gaps can be reduced.

While this study provides a comprehensive analysis of the technology transfer process and the factors influencing its effectiveness, it also has some limitations that suggest directions for future research. For example, the research employed a DEMATEL technique to identify the correlations between the various factors influencing technology transfer. This approach may not account for all the intricacies and subtleties of the process. Additionally, the research centered on a particular sector, and the proposed model's efficacy could differ in other industries. Moreover, the study overlooked the influence of cultural factors and disparities that may impact technology transfer outcomes. These constraints highlight the necessity for additional research to refine the proposed model and tailor it to different industries and cultural backgrounds. Future research could also investigate the influence of various factors, such as intellectual property rights, financing, and market conditions, on technology transfer results.

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