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IMPROVED AHP AND MANIFOLD LEARNING MODEL FOR R&D AND TRANSFORMATION FUNCTIONAL PLATFORM PERFORMANCE EVALUATION

The accurate assessment of R&D and transformation functional platform performance is an important basis for the improvement of high-tech industry competitiveness. In this paper, the authors establish an improved AHP-manifold learning model to solve the problems of the traditional AHP method which needs to satisfy the consistency condition in constructing judgment matrices. In the ranking process of inconsistency of judgment matrices, on the basis of the neighbour distance, the neighbour distance matrices of the data sets corresponding to judgment matrices are constructed first. Next, each data point is mapped to a low-dimensional global coordinate system based on the linear representations of the neighbour points, and the low-dimensional embeddings corresponding to the judgment matrices are obtained. Then the ranking conclusion is obtained by analysing the superiority and inferiority ranking of the elements according to the correspondingly calculated low-dimensional embeddings from each hierarchy. Finally, the proposed method and another numerical method are used to assess R&D and transformation functional platform performance. The result illustrates that the proposed method has a higher level of effectiveness and practicability, and it can provide good guidance for improving platform performance.

Keywords: improved AHP; manifold learning; R&D; transformation functional platform; performance evaluation
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1. INTRODUCTION

R&D and the transformation functional platform, which have been taken as the core organization to accelerate industrial technology breakthrough and achievement transformation, is a powerful complement to high-tech industry clusters. It effectively integrates the resources owned by all links and entities in the high-tech industry value chain, and promotes industrial cooperation in a

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more convenient, effective and safe manner to realize the innovation of high technology chains, the innovation of major product's R&D transformation and service, and the common demand of industrial chain clusters. Therefore, under the conditions to develop harmoniously the commercial ecosystems of high-tech industry and promote its overall competitiveness, to establish an effective high-tech industry functional platform operational performance model is a deep-rooted issue that urgently needs to be solved in the current times, and it is also an important task for the government to guide the cultivation of high-tech industries.

At present, some countries and regions, including the EU, the United States, Japan and South Korea, all regard high-tech industries as strategic pillar industries, and attach great importance to R&D and transformational functional platforms construction and operation optimization. In China, functional platforms such as *Intelligent Internet Alliance Automotive Pilot Demonstration Zone* and *Biomedical Innovation Organization* have been established in some regions, but most platforms are only a kind of *semi-finished products*, and platform's fragmentation phenomenon is prominent. There are many problems in platform development, such as e.g. the need to improve effectiveness, the operation and management mechanism to be optimized, and performance assessment and related mechanism to be perfect. At this stage, the research on R&D and transformational functional platforms are very limited. Eisenmann (2008) proposed a seven-stage model for establishing a R&D and transformational functional platform based on the recognition of regional innovation capabilities, exploration, comparative innovation and knowledge transfer methods. Boudreau (2010) propose that R&D and transformation functional platforms provide a variety of input for different participants through their own governance and management structure, intellectual property rules and operation procedures, so that the platform organization and members can get a better result. Claesson (2006) proposed an evaluation model for functional platforms; this model's emphasis is on the implementation process of industry-university-research cooperation, and the evaluation index system consists mainly in the conversion process input and output elements. Cooke (2012) made a detailed analysis of the platforms' operational mechanism, components, and functional effects from the mutual contact perspective of platform, market, and innovation. Hernandez (2003) put forward an assessment model for platforms based on the aspects of the main participants' service attitude and ability. Xu (2013) pointed out that factors affecting platform performance include resource integration, operation management and operational services, then constructed a platform performance evaluation index system based on these elements.

Like other organizational performance evaluation, the key to R&D and transformation functional platform performance evaluation is to set up an effective evaluation model, including an index system and evaluation method, which directly determine the scientific and effectiveness of evaluation results. However, due to the platform being in the primary development stage, the particularity of R&D and transformation functional platform must be considered, but most of the existing research ignores this.

The particular aspect should be taken into account when setting evaluation indicators. Due to the complexity of the environment, and that the development is still at the stage of exploration, the functional platform performance is affected by many factors, including not only the platform openness, the resource structure, the trust level among the platform members, and the operating mechanism, but also the platform operational policy environment, market environment, benefits of stakeholders, etc. In addition, most of these factors also involve multiple sub-factors, such as the enhancement of stakeholders' benefits, which consists in the increase of operating income, technology maturity, product popularity and competitiveness, so the indicators analysis must be comprehensive in order to fully reflect the performance status of the platform. However, the development of R&D and transformation functional platform are at the initial stage, when setting too many performance indicators in practice will lead to excessive platform operation restrictions, and it is not conducive to accurately identifying key performance and providing effective suggestions for platform's development.

Therefore, considering the complexity of performance affecting factors, in order to make a systematic and efficient evaluation, this paper intends to use system literature analysis method to collect and summarize the indicators. All these indicators were used in platform performance management practice in domestic and foreign countries, especially the area where the functional platform is well established. Next, the characteristics and trends of the performance indicators will be analysed. On the basis of these performance indicators and platform functions, this article will be using large-scale survey questionnaires and the Delphi method to conduct an in-depth research in several Chinese high-tech industrial parks, to build a theoretical model to analyse the high usability and usefulness of influential factors, and finally to determine the performance index system for the platform.

The basic function of R&D and the transformation functional platform is to form a dynamic and stable innovation network among the main innovation subjects to realize effective governance. Its fundamental purpose is to reduce the innovation cost and improve high-tech industry competitiveness. In the research of cooperative R&D, resource sharing, especially knowledge sharing and the innovation network, scholars have put forward many constructive ideas. Based on the previous research, this paper constructs a theoretical model of main effects factors and establishes a platforms' performance evaluation index system based on five factors: resource structure, policy environment, platforms' openness, trust level between the platform and the members, and the contractual governance mechanism. In order to ensure the efficiency of the performance evaluation, the performance index system is only set at two levels. The first level includes: resource structure, policy environment, platform openness, trust level and contract governance mechanism. All the indexes under these five dimensions are second level indicators.

There are some particularities that should be taken into account when constructing evaluation methods. The performance evaluation of R&D and the transformation functional platform is a complex multi-dimensional and multi-variable problem. At the same time, due to the imperfection of platform development and limitation of the evaluator's own conditions, it is difficult for evaluators to grasp the quantitative state of each indicator. Therefore, a combination of qualitative and quantitative, systematic, hierarchical methods is needed to deal with this problem. This paper will use the analytic hierarchy process (AHP) to calculate a platform's performance. AHP has many advantages, and the most important point is simple and clear. AHP not only applies to situations where there is uncertainty and subjective information, but also uses experience, insight, and intuition in a logical way. The greatest advantage of AHP is the presentation of hierarchy, which makes the users consider the indicators' relative importance seriously and deal with complex problems in a practical and effective way.

However, in the actual AHP application process, the judgment matrix given by experts often does not satisfy the consistency condition. How to solve this problem has become the study focus for many researchers. The traditional solution assumed that the main reason for the consistency problem is that the comparison results often have non-objective consistency, so it is necessary to adjust the broken non-conformance matrix automatically or by itself according to certain rules. In line with this idea, scholars at home and abroad put forward various ways to adjust the inconsistent judgment matrix. Wang (2008) applies the *sum product method* to make a consistent ranking of the judgment matrix. Wang (2005) clustered the matrix by means of *system cluster analysis*, and distributed weight coefficient to obtain a consistent matrix based on it. Benitz (2011) proposes to use *orthogonal projection* in linear space to provide a maximum approximate consistency matrix for non-conformance matrices, and achieve consistency through linearization methods. Fan et al. (2001) analyse the nature of fuzzy judgment matrix consistency, and give a *deviation matrix method* to construct consistency matrix. Liu et al. (2011) proposed to use a *niche genetic algorithm* to modify the judgment matrix to obtain consistent result. However, analysing the existing research results, this research finds that although these methods can eventually obtain a consistency matrix, but in the process of adjusting certain element values, there is a big difference between post-adjustment and pre-adjustment, which means the original experts' discriminate information is seriously tampered with. Therefore, the reliability of evaluation conclusions cannot be guaranteed.

The original intention of the AHP method is to use experts' discriminate information to solve the complex decision problem of multi-objective and multi criteria. If the original discriminative information is seriously flawed, it will distort the entire evaluation result, and cannot provide scientific guidance for performance optimization. Based on the above analysis, this paper will propose a method for sorting non-generality judgment matrices, which requires no sensitivity tests, i.e. a non-uniform judgment matrix ranking method based on manifold learning. Manifold learning can fully preserve the original information and avoid deliberately adjusting the value of components to satisfy consistency.

Manifold learning is a combination of differential topology and machine learning. It is a kind of reduction method for nonlinear high dimensional data which has emerged in recent years. In 1995, Bregler and Omohundro first used the term *manifold learning* in the study of Visual Speech Recognition. In 2000, three papers related to it were published in the same issue of "Science Magazine", which triggered the upsurge of manifold learning. The representative techniques include Laplacian Eigen maps (LE), Hessian locally linear embedding (LLE), local tangent space alignment (LTSA), semi-positive embedding(SDE), diffusion mapping (DM), stochastic neighbour embedding (SNE), Riemannian manifold learning (RML), local spline embedding (LSE), etc.

The mathematical description of manifold learning is: set high-dimensional observation data sets as $a=\{a_1,a_2,\cdots,a_n\}$, where $a \subset R^n$. If Y is a d-dimension embedded and Y$\subset$Euclidean space R^4, then $f:Y \to R^n$ is a smooth embedding mapping, and $n >> d$. The object of manifold learning is to use high-dimensional observation data set $a = f(Y)$ in R^n to find out the low-dimensional embedding Y and embedded mapping f corresponding to the high-dimensional observation data set. The locally linear embedding method can effectively preserve the inherent geometric structure of the i element in the rating system, that is, to retain the order relationship between the i element and the other elements, so the use of manifold learning can achieve the optimal sorting of the evaluation scheme to be measured. In essence, the noncongruent judgment matrix ranking method based on manifold learning is still an analysis method based on the experts' subjective preferences, and its most important comparative advantage is to reflect the expert's opinion more accurately and truly, and to retain the expert's original information completely.

The article is arranged as follows. The first part analysis the functional platform's operational mechanism and ecological environment, and builds a performance index system. The second part analysis the principle and existing problems of the AHP method. The ordering ideas and implementation steps of the non-uniform judgment matrix ranking method based on manifold learning is given in the third section. The fourth section presents case analysis, and conclusions are given in the fifth section.

2. CONSTRUCTION OF R&D AND TRANSFORMATION FUNCTIONAL PLATFORM PERFORMANCE INDEX SYSTEM

2.1. The theoretical model of platform operation performance influencing factors

The operational performance of R&D and transformation functional platforms can be characterized by two modules: service performance and network performance. All these are affected by the factors of platform resource structure, trust level, platforms' openness, contract governance mechanism, and policy environment. Based on the previous research (Hernandez, 2003; Harmaakorpi, 2006; Gassmann, 2006; Claesson, 2006; Eisenmann, 2008; Boudreau, 2010; Petrusson, 2010;Cooke, 2012; Fang, 2017; Xia, 2017) and a platform's construction practice, this project analyzes the factors influencing R&D and transformation functional platform performance from the viewpoint of the above five aspects.

(1) Resource structure

The platform's scientific and technological innovation resources and structures, which are gathered by itself and its members, have an important impact on their own operational performance. The resource structure mainly depends on the quality of the platform's members, which refers to the number and quality of the members' capabilities, innovation resources, cooperation experience, and reputation in the field of technology research and development. The quality of the members is of great significance for them to achieve their goals, it directly determines the value of their cooperative R&D partners development system, scientific and technological achievements transfer system and knowledge sharing system, thereby affecting the platform's operational performance.

The research literature on strategic alliances shows that the basis for obtaining more cooperation is to make reasonable choices of partners. The significance behind this is that the success of strategic alliances depends on the quality of partners' resources. Fang (2017) found that the main purpose of establishing strategic alliances or cooperation between enterprises is to share or exchange scarce resources, and therefore puts high demands on the partners. The value created by the cooperation parties through the accumulation of resources exceeds the sum of the value created by each enterprise, which results in a joint resource advantage. Xia and Tan (2017) clearly stated that the selection of partners should consider their resources status and believe that the partner's potential resources have an important impact on cooperation performance. For high-tech industries, how to effectively acquire knowledge and complementary resources in the process of technology development and commercialization is one of the major challenges. This is also the main motivation for innovative entities in the high-tech industry chain to join and use functional platforms. Therefore, to study the influencing factors of platform performance, one must take the platform's resource structure into consideration.

(2) Trust level

Trust refers to a state that is willing to accept some kind of vulnerability based on the positive expectations of other people (Krukow, 2006). Most studies believe that trust among members is a key factor for the success of R&D alliances (Bidgoly,2015). Trust can make it easier for members to reach a consensus on cooperation, i.e. all the parties believe that their gains obtained from cooperation will be significantly greater than the gains made by themselves. This will increase the expectations of successful cooperation and in turn encourage long-term cooperation, and ultimately benefit the resources transfer, exchange, and sharing. Nogoorani (2016) believe that trust can reduce members' worries regarding their partners' opportunistic behaviour, increase probability of cooperation and improve its quality. The studies of Reece (2007) show that trust can reduce conflicts and cooperation management costs. Sabater (2002) believes that trust helps partners coordinate with each other to respond to the environment changes, thereby reducing innovation risk and improving cooperation flexibility and resilience. In the study of alliance knowledge sharing, Tang (2004) found that trust is an important basis and determinant factor of knowledge sharing. Pan and Li (2008) used the structural equation model to make an empirically study and confirmed that trust between members has a significant impact on the performance of strategic alliances. Trust shows that members are willing to share valuable innovative resources with their partners, including secret information and tacit knowledge, and are willing to bear the corresponding risks. Trust also means that without the supervision, partners will not use their weaknesses to seek other interests.

The relationship within the platform and its members is cooperative, and trust is the prerequisite and foundation for the success of this cooperation. In the literature about strategic alliances and cooperative R&D, trust has always been regarded as an important factor influencing the cooperation stability and performance (Tang and Chen, 2004; Teacy, 2012). The main operating mechanism of the R&D and transformation functional platform is through cooperative R&D partnership development, scientific and technological achievement transfer, and resource sharing to provide services for members. When accepting the services provided by the platform and other members, they must trust their service capabilities and service levels, i.e., trust them. The more members trust the platform, the more willing they are to share their own knowledge, information and other innovative resources, and to believe and accept the information, knowledge and information provided by other members.

(3) Platform openness

The openness of R&D and transformation functional platforms mainly refers to the relevant entities in the high-tech industry chain who can join the platform and who have the right to use the platform's resources and services (Petrusson *et al.,* 2010). Under the restriction of resources and ability, the innovation subject in the high-tech industry chain cannot obtain the information, knowledge, and capabilities within its organization only, they have to seek cooperation in every link of the industrial innovation chain. The open innovation proposed by Chesbrough (2003) provides a brand-new innovation management model for the innovation subject in the high-tech industry to break through the bottleneck of innovation. The innovative subjects joining the functional platform are intent on using the innovation network and related services provided by the platform to establish more extensive contacts with potential innovative partners. Through this, they can obtain more knowledge, capabilities and other innovation resources necessary for innovation. Jonsson (2010) clearly pointed out that the degree of platform's openness has a significant impact on the high-tech industry members to participate and use the platform.

The existing high-tech industry R&D and transformation functional platforms at home and abroad generally provide different conditions for joining. For example, the Bio-Open Source Platform (BIOS), whose main purpose is to share intellectual property, knowledge, and technology, imposes certain restrictions on joining and using the resource. The EU innovation, IMI, with the main purpose of promoting cooperative R&D alliances, does not set any restrictions on the membership, any enterprise or scientific research institution can apply to join, various resources for platform convergence are also open to all members. Setting certain conditions, the final result must influence the platform's attractiveness and the operational performance.

(4) Policy environment

High-tech industry is a science and technology innovation-driven industry, which is highly regulated by government. The government's support policies, laws and regulations, and infrastructure construction policies have an important impact on their development. In studying the policy environment of China's high-tech industry innovation, Acs (2007) believes that China's high-tech industry is undergoing a period of significant policy changes, and the biggest impact policy for them is the market supervision policy and innovation support.

At present, governments in various countries are vigorously strengthening relevant laws and regulations of high-tech industries. For example, in the area of smart car technology R&D laws and regulations, the United States, Europe, Canada, Japan and Australia have imposed mandatory regulations on installations at certain time points to promote the smart driving penetration rate. No matter how mature the technology is, there will be a seemingly insurmountable barrier before the bright future of unmanned regulations. The promotion of laws and regulations is not only directly and positively related to the assembly rate of smart components, such as ADAS, but also is an important part of boosting unmanned driving.

Scientists who study strategic alliances believe that the integration of knowledge and innovation resources between independent corporate entities is essentially the exchange of resources among members and plays a different role in the value chain (Porter, 1996). It is through their partner development system, knowledge sharing system, scientific and technological achievements transfer system that functional platforms facilitate the R&D cooperation and technical transactions among members. Thus, various taxes and fees in the transaction process are bound to impact on the platform performance. Turnover taxes constitute a main taxation source in China. Every statutory transaction that occurs between different entities must pay tax or sales tax according to the law, especially when it comes to the development of business tax on service outsourcing and technology transactions. Generally, it cannot be deducted, nor can it be included in the enterprise's intangible assets for annual depreciation. These taxes and fees generated by the transaction process, especially non-deductible taxes, like business tax, will hinder the deepening of labour division among enterprises, thereby reducing cooperation opportunities among platform members and adversely affecting platforms performance improvement.

(5) Contract governance mechanism

During the process of functional platforms operation, the platform and its members need to select appropriate contract governance mechanisms to guide all parties' activities and reduce the cooperation risks. When studying the strategic alliances, Lusch (1996) found that contract control can effectively reduce the risk of the alliance's relationship and thus facilitate knowledge sharing.

According to transaction cost theory, a highly comprehensive contract governance mechanism can effectively promote knowledge sharing in the platform. A well-completed contract governance mechanism can reduce platform system vulnerability and reduce opportunistic behaviour, thus helping to guide cooperation among the members. The contractual governance mechanism can also effectively reduce conflicts which may jeopardize cooperation, because a clear contract can provide a clear institutional framework for the rights and obligations of parties as well as the basic principles and main procedures for resolving conflicts between two parties (Gedell, 2011). By helping parties to clarify their own responsibilities, interests and needs, the contractual governance mechanism can also coordinate the common goals and reduce cooperation management complexity (Yu, 2011). When studying the knowledge sharing among strategic alliances, Huang (2016) proposed that a complete contract not only helps to clarify the partners' interests, but also punishes their opportunistic behaviour. Rui (2007) pointed out that some main issues such as cooperation rules, main cooperation methods, corresponding cooperation process and formal contract mechanism etc., can be clearly defined in the contract terms in advance, which will help all parties to carry out knowledge exchange and sharing smoothly. A formal contract mechanism that clearly defines all parties' rights and obligations not only can significantly reduce the coordination costs, but also help to improve knowledge sharing efficiency. More importantly, the platform's advantages in hardware conditions need to be integrated by governance mechanisms. That is, a perfect governance mechanism will also regulate the relationship between other factors and platform performance.

In summary, resources structure, trust level, platform's openness, contract governance mechanism and policy environment all have an important influence on a platform's operational performance. Resources structure directly determines a platform's resource status and service capabilities. The level of trust impacts on the process of providing services, such as cooperative innovation, knowledge sharing and transforming technology service. Platform openness has a significant impact on innovation network expansion. The government's policies on taxation, supervision, and intellectual property protection are important environmental factors for platforms, and will have an impact on the platforms' operational performance. The contract governance mechanism is the main tool for regulating the interest relationship between the platform and its members, and it will not only directly affect platform's operational performance, but also affect platform's resources structure and its openness. To this end, this paper establishes a theoretical model for the performance factors of R&D and transformation functional platforms, as illustrated in Figure 1,where one can see that resources structure, platform's

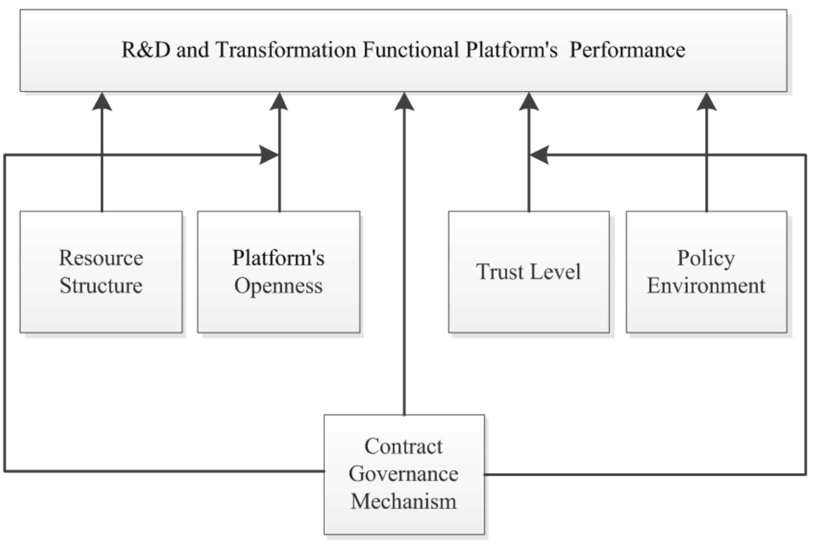

Fig.1. Model of R&D and transforming functional platform performance impact factors

Source: The author organizes according to relevant information.

openness, contract governance mechanism, trust level and policy environment all have a direct impact on a platform's performance. In addition, the platform's governance mechanism will also affect the platform performance indirectly by affecting resources structure, trust level, platform's openness, contract governance mechanism and policy environment.

2.2. Performance evaluation index system construction

(1) Indicators of resource structure

For high-tech industries, how to effectively acquire knowledge and complementary resources in the process of new technologies development and commercialization is one major challenge. Obviously, members with more unique resources and knowledge are more attractive to potential partners and more likely to meet their innovative needs (Fang, 2017; Xia and Tan 2017; Cho, 2008). The higher the degree of platform's resources structure optimization, the stronger the platform's service ability, and the more cooperation opportunities created for the members. Past experience in cooperation has also helped companies deal with their relationships with partners, thereby facilitating mutual learning and cooperation (Makipaa, 2011). In addition, the high reputation of the partners also means their higher quality.

Based on the research of e.g. Xia and Tan (2017); Medema (2011); Fang (2017), this paper selects the following four items from the perspective of members' quality to measure the resources structure: whether the members have a good reputation in the related field; whether they have strong research and development capabilities; whether they have rich innovation resources; whether the members have rich experience in cooperation.

(2) Indicators of trust level

When examining the practical experiences of foreign R&D and transformation functional platforms, it was found that one important reason why members join platforms is that they believe in the platform's capabilities of resource integration and service provision. On the one hand, the platform is invested and supported by the government. On the other hand, the platforms have contributed to the success of many member enterprises, so that the platform and members have the trust foundation. The trust level is a key factor in the success of R&D alliances and functional platforms (Teacy, 2012; Boudreau, 2010). In accordance with the existing literature (Sabater, 2002; Tang, 2004; Krukow, 2006; Reece, 2007; Bidgoly, 2015; Nogoorani, 2016) this paper mainly uses the following four items to measure the trust level: whether the members maintain a long-term friendly relationship; whether they trust the information provided by others; whether they trust the services provided by others; whether they maintain good communication.

(3) Indicators of platform's openness

When investigating Shanghai BeiDou Navigation R&D platform, it was found that most of the data and literature resources gathered by the platform can be used by all the registered members. However, certain conditions have been set for joining, including the site of registration and operation must be in Shanghai, the applicant must have certain scientific and technological resources and agree to provide external shared services. Synthesizing the research Pernilla *et al.* (2015) and Petrusson *et al.* (2010) on platform openness, this article uses the following three items to measure whether the restrictions on joining are relaxed; whether the restrictions on resources using are relaxed; whether the restrictions on services provided are relaxed.

(4) Indicators of policy environment

Policy environment is the foundation for establishing functional platforms and ensuring it achieves the goals. When inspecting the operational performance of high-tech industry R&D and transformation functional platforms, the policy environment is an influential factor that must be considered. Based on the research of Porter (1996), Acs (2007), and Petrusson *et al*. (2010), this article uses the following four items to measure policy environment: whether there is a perfect intellectual property protection system; whether there is a perfect legal and regulations system; whether there is a perfect tax system; whether there is a perfect research support policy.

(5) Indicators of contract governance mechanism

In the process of the platform providing services to its members, or in the process of cooperative R&D, the sharing of resources, or trading of scientific and technological services, all parties must choose a reasonable governance mechanism to exercise restraint, encouragement and balances, to ensure the effective operation of functional platforms and their respective interests. The contractual governance mechanism consisting in a series rule contract system for the platform and its members. These contracts summarize what the platform and its members can and cannot do, and the associated consequences. Based on the research by Lusch (1996), Luo (2009), Rui (2007), Zvolinschi (2008), this article uses the following four items to measure the contract governance mechanism: whether the platform has a complete resource sharing mechanism; whether it has a complete income distribution mechanism; whether it has a complete cost sharing mechanism; and whether the platform governance has a complete execution mechanism.

On the basis of the above analysis, the performance evaluation index system for R&D and transformation functional platforms constructed in this paper is shown in Table 1.

Table 1

Performance Evaluation Index System for R&D and Transformation Functional Platforms

First-level indicators	Secondary indicators	Nature of indicators
Resource Structure C_1	Member Reputation C_{11}	Qualitative
	Member R&D Capabilities C_{12}	Qualitative
	Member Innovation Resources C_{13}	Qualitative
	Member Cooperation Experience C_{14}	Qualitative
Trust Level C_2	Cooperation Relationship C_{21}	Qualitative
	Information Sharing C_{22}	Qualitative
	Service Level C_{23}	Qualitative
	Communication Status C_{24}	Qualitative
Platforms' Openness C_3	Restrictive Conditions for Joining C_{31}	Qualitative
	Restrictions on the Utilization of Platform Resources C_{32}	Qualitative
	Restrictions on the Service Provision C_{33}	Qualitative
Policy Environment C_4	Intellectual Property Protection System C_{41}	Qualitative
	Law and Regulation System C_{42}	Qualitative
	Tax System C_{43}	Qualitative
	Research Support Policy C_{44}	Qualitative
Contract Governance Mechanism C_5	Resource Sharing Mechanism C_{51}	Qualitative
	Income Distribution Mechanism C_{52}	Qualitative
	Cost Sharing Mechanism C_{53}	Qualitative
	Implementation Mechanism C_{54}	Qualitative

Source: own elaboration.

This study establishes a performance evaluation index system based on the factors affecting the platforms' performance. The rationality and feasibility are as follows. First, the performance evaluation index system based on the impact factors emphasizes the importance of multi-dimensional collaborative evolution to technological innovation. The five dimensions indicators can transform platform strategic objectives into stages, specific and executable goals, and make the whole goals definitely clear. At the same time, all these five dimensions indicators take the key links in the performance realization process into account, and make the core control points of each dimension clear. Second, the performance evaluation index system based on key performance factors can achieve the convergence of performance processes to the greatest extent, and realize a closed loop in performance management practice.

3. IMPROVED AHP MANIFOLD LEARNING METHOD FOR PLATFORM PERFORMANCE EVALUATION

3.1. AHP method principles and problem analysis

The key to the AHP method is to construct a judgment matrix between the related levels, and use the weights calculated by the judgment matrix to rank the elements of each level. The constructed judgment matrix must satisfy the consistency condition. The smaller the *CR* (consistency ratio), the less the judgment matrix deviates from the consistency. As a rule of thumb, Saaty (1980, 1987) suggests that when the consistency ratio is less than or equal to 0.1, it is considered that the judgment matrix is consistent.

The consistency of the judgment matrix includes basic consistency and order consistency. Set $A=(\alpha_{ij})$ as an n-order reciprocal judgment matrix. If the elements in *A* satisfy: for any i, j, k, ① if $a_{ij}>1, a_{jk}\geq 1$ or $a_{ij}\geq 1, a_{jk}>1$, then $a_{ik}>1$; ② $a_{ij}=1, a_{jk}=1$, then $a_{ik}=1$; *A* is said to have order consistency. If $a_{ik}\cdot a_{kj}=a_{ij}$, *A* is said to have basic consistency, or *A* is said to be consistent. Obviously, if the reciprocal judgment matrix *A* is consistent, it must have order consistency, that is, the ordering results are preserved under strong conditions. So it can be found that if $W=\left[w_1,w_2,\cdots,w_n\right]^T$ is the sorting vector of *A*, the necessary and sufficient condition for the positive reciprocal matrix *A* to be the consistency matrix is $a_{ij}=w_i/w_j,\quad i,j\in N$.

The use of AHP adjusts the non-uniform judgment matrix to achieve order preservation under strong conditions. Wei and Zhang (2007) pointed out that under a single criterion, if a method is ordered, then this method can reflect the objective ordering of the program. It can be seen that all the adjustments of the judgment matrix, although on the surface meant to realize judgment matrix consistency, but their ultimate aim is to reflect the objective type of the program. How to construct a method with an order-preserving nature and effectively rank the non-uniform judgment matrix will be the core purpose of this paper.

According to the research of Saaty (1980), in order to obtain an effective ranking result, the judgment matrix needs to satisfy three conditions: ① $a_{ij}>0$; ② $a_{ij}=1/a_{ji}$; ③ $a_{ij}\cdot a_{jk}=a_{ik}$. However, in the actual decision-making process, it is generally difficult to satisfy all the above conditions at the same time. Certain adjustments to the judgment matrix are required, but the adjustment process will produce a large number of problems. The following will specify the situation. When the judgment matrix A does not satisfy the above conditions, it is necessary to adjust it. However, the existing adjustment method will discard the original discriminate information given by the expert to meet the consistency requirement, making the change amplitude of element values in the matrix and the sorting result too large. Specific examples are as follows:

Example 1. Set the judgment matrix A to:

$$A = \begin{bmatrix} 1 & 1/9 & 3 & 1/5 \\ 9 & 1 & 5 & 2 \\ 1/3 & 1/5 & 1 & 1/2 \\ 5 & 1/2 & 2 & 1 \end{bmatrix}$$

By calculating the consistency ratio $CR = 0.345 > 0.1$, it was found that there is no consistency. Using the angle cosine method proposed by Chen and Fan (2004) to correct, we obtained the correction matrix:

$$A_1 = \begin{bmatrix} 1 & 1/9 & 1/2 & 1/5 \\ 9 & 1 & 5 & 2 \\ 2 & 1/5 & 1 & 1/2 \\ 5 & 1/2 & 2 & 1 \end{bmatrix}$$

The corresponding ranking weight vector is: $(0.0583, 0.5528, 0.1202, 0.2687)$.

Using the induced matrix method proposed by Hu *et al.* (2015) to correct the obtained correction matrix:

$$A_2 = \begin{bmatrix} 1 & 1/9 & 1 & 1/5 \\ 9 & 1 & 5 & 2 \\ 1 & 1/5 & 1 & 1/2 \\ 5 & 1/2 & 2 & 1 \end{bmatrix}$$

The corresponding ranking weight vector is: $(0.0723, 0.5527, 0.1048, 0.2688)$.

Compared with the above matrix A_2, it can be seen that the adjustment margin of the judgment matrix is too large. Some of the existing weight relationships have been completely negated, the original expert opinion was partially abandoned, and the ranking results have also undergone major changes. The rationality of the adjustment program is difficult to accept, and the adjustment of judgment matrix is too complex. When the conformance requirements are not met, the non-congruent elements must first be found, and then it should be adjusted repeatedly to obtain a consistency judgment matrix. In the actual application process there is a large number of judgment matrices, and also a large number of matrices that do not meet the consistency requirements, this will also bring higher complexity of adjustment. It can be seen from Example 1 that the number of judgment matrices required to be dealt with in the decision problem is 1, and the maximum number of elements that may need to be adjusted is 16. When making decision analysis for complex project problems, the size of the judgment matrix that does not conform to the consistency requirement is larger and needs to be repeatedly tested and adjusted. This leads to a continuous increase in computing time and a continuous decrease in user satisfaction, therefore one must consider simplifying the calculation process and changing the sorting idea to ensure decision process effectiveness.

3.2. Non-uniform judgment matrix ranking method based on manifold learning

Locally linear embedding (LLE) is a local-preserving manifold learning algorithm. The basic idea is to hypothesize that the low-dimensional manifold where the data set is located and its mapping in the high-dimensional observation space are locally linear, by keeping the local linearity constant to achieve dimension reduction. The local linear relationship in the LLE algorithm is represented by a linear combination of neighbourhood sample points. The specific steps are as follows:

Step 1. Select neighbourhoods. Given a data set $a=\{a_1,a_2,\cdots,a_N\}$, where $a_i \in R^D$, $i=1,2,\cdots,N$, N is the total number of data points, search for the nearest k neighbours $\{a_{i1},a_{i2},\cdots,a_{ik}\}$ ($a_{ik} \in X$, $k<N$) for each data point a_i.

Step 2. Calculate the weight matrix $W=\left(W_{ij}\right)_{i,j=1}^{N}$ defining linear reconstruction error function:

$$\psi(W)=\sum_{i=1}^{N}\left\| a_i-\sum_{j=1}^{k}W_{ij}a_{ij}\right\|. \tag{1}$$

If a_j does not belong to the neighbourhood of a_i, set $W_{ij}=0$, otherwise, under the condition of $\sum_{j=1} W_{ij}=1$, one can get weight matrix $W=\left(W_{ij}\right)_{i,j=1}^{N}$ according to formula (1).

Step 3. Solve low-dimensional embedding. Define cost function of low dimension embedding space:

$$\varphi(\mathrm{Y})=\sum_{i=1}^{N}\left\| y_i-\sum_{j=1}^{k} W_{ij} y_{ij}\right\|^2. \tag{2}$$

Considering the constraints $\sum_i y_i=0$ and $\sum_i y_i y_i^T / N=I$, the low-dimensional embedding can be solved by the following formula:

$$Y^*=\arg\min_Y \varphi(\mathrm{Y}). \tag{3}$$

From (2), the low-dimensional description of the data is translation-invariant, so the solution of Y is indefinite. In the third step, add constraint $\sum_i y_i=0$ to eliminate the influence of translation invariance, add $\sum_i y_i y_i^T / N=I$ to prevent the data set collapsing to a point in low dimension. Thusthe least squares problem solved by equation (3) is transformed into

$$Y^*=\arg\min_Y \varphi(\mathrm{Y})=\arg\min_Y \sum_{i=1}^{N}\left\| y_i-\sum_{j=1}^{k} W_{ij} y_{ij}\right\|^2=\arg\min_Y \left\|(\mathrm{I}-\mathrm{W})\,\mathrm{Y}^T\right\|_F^2$$
$$=\arg\min_Y tr\left[Y(\mathrm{I}-\mathrm{W})^T(\mathrm{I}-\mathrm{W})\,\mathrm{Y}^T\right]. \tag{4}$$

The above equation is equivalent to the spectral decomposition problem. Finding the optimal solution of Y^* is equivalent to finding the feature vector corresponding to a set of minimum eigenvalues of the matrix $(\mathrm{I}-\mathrm{W})^T(\mathrm{I}-\mathrm{W})$.

In the AHP method, the mathematical expression of the judgment matrix is:

$$A=\begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{n1} & \alpha_{n1} & \cdots & \alpha_{nn} \end{bmatrix}.$$

Judging from the mathematical thinking of manifold learning, the judgment matrix A can be considered as a storage form of data set α. If one regards the i-throw in the judgment matrix A as a set of weight ratios given by experts based on the evaluation scale for the i-th element, then the weight ratio of the group reflects the position of the i-th element relative to the other elements in the evaluation system. Therefore, the element $a_i = \{a_{i1}, a_{i2}, \cdots, a_{ik}\}$ in the i-th row of the matrix A can be considered as the coordinate value of the i-th element in coordinate system. The coordinate system E is a coordinate system which takes n weight ratios as the coordinate axes, and takes the n weight ratios (when both are zero at the same time) as the coordinate origin 0. Using local linear embedding method to make a dimensionality reduction of multidimensional data points in data set $a = \{a_1, a_2, \cdots, a_n\}$, one obtains the corresponding low dimensional data points Y. Since in the local linear embedding method, the low-dimensional data point Y is called low-dimensional embedding, for a convenient narrative in the following, it will be called low-dimensional embedding $\mathrm{Y} = (\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_n)$. The LLE method can effectively retain the i-th element in the rating system, i.e. it preserves the ordinal relationship between the i-th element and other elements (as will be demonstrated in detail below). Then the manifold learning can be used to optimize the rank of the evaluation program to be measured. The specific sorting principle is shown in Figure 2:

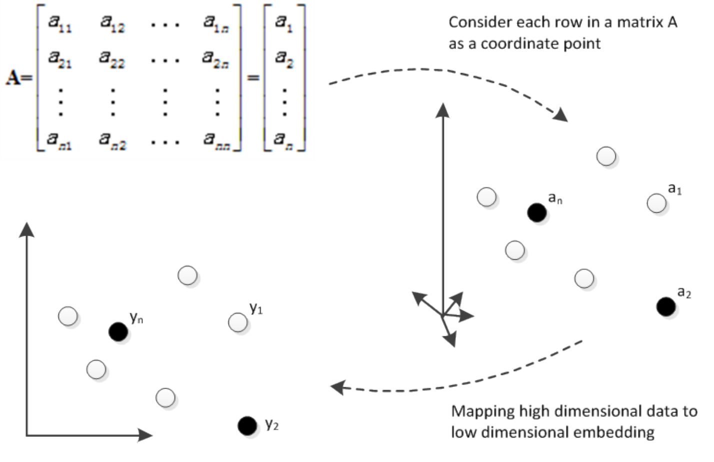

Fig. 2. Schematic diagram of non-uniform judgment matrix ranking method based on manifold learning

Source: Drawing on previous studies.

Based on the above ideas, this paper proposes to use the weight ratio of judgment matrix as the coordinate information, and use the local linear embedding method as the dimension reduction tool. Based on this, the use of manifold learning establish a non-uniform judgment matrix ranking method. According to the sorting principle diagram, the key of the proposed method is to find the low-dimensional embeddings Y that correspond to data set α (i.e. take the judgment matrix Y as a storage form of α). In the following, the local linear inlay method will be applied to this problem to achieve low-dimensional embedding.

The weight ranking of the traditional AHP method is based on the condition of $a_{ij} \cdot a_{jk} = a_{ik}$. By using the $Ag = \lambda g$ formula in linear algebra (g is a non-zero n-dimensional vector, λ is constant), calculate the eigenvector corresponding to maximum characteristic root accurately (the eigenvector is the weighted order of this layer element). However, the non-uniform judgment matrix ranking method based on manifold learning discards the constraint condition of $a_{ij} \cdot a_{jk} = a_{ik}$, and adopts an element sorting strategy based on nonlinear dimensionality reduction, which depends on the discriminate information directly given by experts. Therefore, the non-conformance judgment matrix ranking method based on manifold learning has obvious advantages: it overcomes the compulsive influence of the relevant elements and reflects the constructor's real intention.

Combining the above ideas, the specific implementation steps of sorting the nonconforming matrix based on manifold learning are as follows:

Step 1. Select the key affecting elements, and establish a multi-level model with clear relationships based on the correlation between the elements.

Step 2. Make a comparison between a certain element a_i in the upper layer and all the elements in the next layer which is connected with a_i, the values are assigned according to the 1-9 scale method, construct an $n \times n$ judgment matrix A. Based on A and the low-dimensional embedding sorting algorithm given above, take the data set $a = \{a_1, a_2, \cdots, a_{n-1}, a_n\}$ corresponding to the judgment matrix as the input value, obtain the low-dimensional embedding Y, and normalize the low dimensional embedded vector $y_i (i = 1, 2, ..., n)$ in Y.

Step 3. Determine the ranking scheme for the total goals on the basis of solving low-dimensional embedding at each layer. Set the low-dimensional embedding vector of the upper layer element as y_j^a (a is the number of highest layer, $(j = 1, 2, ..., n)$). The low-dimensional embedding vector of the lower element to the upper element is denoted by y_{ij}^b (b is the number of the upper layer, $(i, j = 1, 2, ..., n)$). Then the low-dimensional embedding vector of the elements at next level to the total goal is:

$$y_i = \sum_{j=1}^{n} y_j^a y_{ij}^b b, \quad (i = 1, 2, ..., n). \tag{5}$$

Rank the program according to the size of y_i, and select the scheme with the largest value of y_i as the optimal scheme.

It is important to point out that the manifold learning ranking method is also an analytical method to solve multi-attribute decision problems based on the experts' subjective preferences. Although it still needs to build a multi-level model and judgment matrix compared to the traditional AHP method, in essence its most important comparative advantage lies in its ability to more accurately and truly reflect the expert's discriminating opinions, completely retaining the expert's original information and using it for decision analysis.

3.3. Theoretical analysis of the advantages of non-uniform judgment matrix ranking method based on manifold learning

Similar to other manifold learning algorithms, the locally linear embedding method uses the k-nearest neighbours method (or the ε-nearest neighbour method) to determine the adjacency relationship between any two data points in the data set, and assumes that any data point on a manifold can be represented linearly by its neighbours. Since the linear relationship remains unchanged during the mapping process, the high-dimensional observation data can be mapped to a unified global low-dimensional coordinate system, thereby effectively revealing potential low-dimensional embedding in limited high-dimensional data. Foreign scholars have given some conditions for embedding mappings in any high-dimensional data sets. From the above description, it can be found that the local linear interpolation method tries to find the embedded mapping f between the high-dimensional observation dataset and the low-dimensional embedding. According to the embedding definition in traditional differential geometry, if $f: Y \to a$ is a single shot and is a homeomorphism from Y to its image set $f(Y) = a$, then f is an embedded map. It can be seen that the essence of local linear embedding method is to establish a home-omorphism with a low-dimensional smooth manifold in the high-dimensional Euclidean space. Calabrese (2013) pointed out that the two spaces of homeomorphism are actually two spaces with the same topological structure, namely the homeomorphism relationship is an equivalence relationship.

The author will test whether manifold learning is preserved as follows:
Step 1. Set f as an embedded mapping for low-dimensional embedded Y to R^n, and data set a as an image of low-dimensional embedding Y. According to the embedding definition in traditional differential geometry, if f is an embedding map, then f is a homeomorphism from Y to its image set $f(Y) = a$, then Y is homeomorphic to a.
Step 2. If f^{-1} is an inverse function of f, and the embedded mapping f is a one-to-one mapping (i.e. f is single and full shot), then f^{-1} is a one-to-one mapping, too; because both f^{-1} and $(f^{-1})^{-1} = f$ are continuous, so f^{-1} is a homeomorphism. From the above discussion one can see that, since $f^{-1}: a \to Y$ is a single shot and is a homeomorphism from a to its image set $f^{-1}(a) = Y$, so f^{-1} is also an embedded map.
Step 3. Set Y as the low-dimensional embedding of the data set a in manifold learning, i.e. there is an embedding map $f: Y \to a$.

From Step 1 and Step 2 one can see that $f^{-1}: a \to Y$ is also an embedding mapping, and is a homeomorphism from a to Y, among them, the elements in a and in Y are corresponding one by one. Based on the research of Crimimisi (2011), it can be seen that if there is a total order relationship $<_a$ of a, there is also a total order relationship $<_Y$ of Y. Therefore, there is an order-preserving mapping between a and Y, that is, the embedded mapping f.

According to the above proof, it can be found that in the learning process of manifold learning, there is a low-dimensional embedding Y corresponding to the data set a. Through Step 3, it can be seen that low-dimensional embedding Y can effectively preserve the order relationship between data points in the original data set, i.e. manifold learning has order preservation. Therefore, according to Wei and Zhang (2007), applying manifold learning to the calculation of judgment matrix A can fully reflect the scheme objective ranking.

4. IMPLEMENTATION OF THE PERFORMANCE EVALUATION MODEL WITHIN R&D AND TRANSFORMATION FUNCTIONAL PLATFORM

Based on the data from the China Economic and Social Big Data Research Platform, the China National Intellectual Property Office, and the Annual Report of Shanghai Science and Technology Creation Center, six industry experts were employed to evaluate the performance of R&D and transformation functional platforms. When assessing each indicator, it is inevitable that this will produce some subjective judgments. In order to reduce errors as much as possible, this study selects semantic judgments to let experts fully express their will. The 1-9 scale method is used to construct a pairwise judgment matrix A between factors in each layer. Among them, α_{ij} is the importance degree of indicator i to indicator j, satisfying $\alpha_{ij} > 0$, $\alpha_{ij} = 1/\alpha_{ji}$, $\alpha_{ii} = 1$. The comparison of the relative importance between factors at the first level and the second level were given by the 6 experts based on the Delphi method (Table 2), and the evaluation matrix and judgment result can be calculated.

Table 2

The comparison of the relative importance between factors

Comparison	Evaluate	Comparison	Evaluate	Comparison	Evaluate	Comparison	Evaluate
C_1/C_2	1/3	C_{11}/C_{12}	1/3	C_{22}/C_{23}	5	C_{42}/C_{43}	3
C_1/C_3	5	C_{11}/C_{13}	1/3	C_{22}/C_{24}	3	C_{42}/C_{44}	1/3
C_1/C_4	1/3	C_{11}/C_{14}	1/5	C_{23}/C_{24}	1/3	C_{43}/C_{44}	1/3
C_1/C_5	1/3	C_{12}/C_{13}	3	C_{31}/C_{32}	1/5	C_{51}/C_{52}	1/7
C_2/C_3	3	C_{12}/C_{14}	1	C_{31}/C_{33}	1/3	C_{51}/C_{53}	3
C_2/C_4	3	C_{13}/C_{14}	5	C_{32}/C_{33}	5	C_{51}/C_{54}	1/5
C_2/C_5	1/3	C_{21}/C_{22}	1/3	C_{41}/C_{42}	3	C_{52}/C_{53}	1/3
C_3/C_4	1/3	C_{21}/C_{23}	5	C_{41}/C_{43}	5	C_{52}/C_{54}	1/3
C_3/C_5	1/5	C_{21}/C_{24}	1/3	C_{41}/C_{44}	1/5	C_{53}/C_{54}	1/7
C_4/C_5	3						

Source: own figure.

4.1. Numerical calculation

In order to compare the advantages and disadvantages of the method proposed in this paper with the existing AHP method, the author used manifold learning, the sum product method and the deviation matrix method to sort the weights of the judgment matrix A. The main calculation process is as follows.

$$A = \begin{bmatrix} 1 & 1/3 & 5 & 1/3 & 1/3 \\ 3 & 1 & 3 & 3 & 1/3 \\ 1/5 & 1/3 & 1 & 1/3 & 1/5 \\ 3 & 1/3 & 3 & 1 & 3 \\ 3 & 3 & 5 & 1/3 & 1 \end{bmatrix}$$

(1) Use manifold learning to calculate the judgment matrix A of the primary indicators and the judgment matrix A_i of the secondary indicators.

According to Step 2 of the non-coherence judgment matrix ranking method based on manifold learning, the nearest neighbour distance matrix is obtained through the ε-nearest neighbour method. The specific comparison results illustrate in the following neighbour distance matrix ND:

$$ND = \begin{bmatrix} 0 & 21.9652 & 20.3976 & 19.8302 & 16.9635 \\ 21.7641 & 0 & 20.0314 & 18.8102 & 19.0074 \\ 20.0893 & 18.7125 & 0 & 20.1543 & 17.1509 \\ 19.1342 & 18.9112 & 19.9813 & 0 & 23.0411 \\ 18.3217 & 18.4744 & 15.9322 & 23.031 & 0 \end{bmatrix}$$

After analysis, a set of neighbours for each data point is constructed. Based on this, function $\Phi(\mathrm{W})$ is used to calculate a matrix W composed of five two-dimensional vectors $W_{ij}(j = 1,2)$, where each two-dimensional vector $W_{ij}(j = 1,2)$ corresponds to a data point $a_i\,(\mathrm{i} = 1,2,3,4,5)$.

$$W = \begin{bmatrix} 3.4271 & -2.3172 \\ 1.5074 & -0.3945 \\ 3.2743 & -1.5861 \\ 1.0834 & 0.1965 \\ 1.4278 & -0.1998 \end{bmatrix}$$

Bringing each row of the k-dimensional vector W_{ij} in the matrix W into the function $\Phi(\mathrm{Y})$, the low-dimensional embedding vector $\mathrm{y}_i\,(\mathrm{i} = 1,2,3,4,5)$ in the low-dimensional embedding Y can be obtained as follows:

$$\mathrm{Y} = \begin{bmatrix} 1.5243 & -1.0716 & -0.3657 & -0.3724 & -0.1962 \end{bmatrix}.$$

Normalize the low-dimensional embedding vector y_i to obtain the norma-lized low-dimensional embedding $\bar{Y}$:

$$\bar{Y} = \begin{bmatrix} 0.5032 & 0.2992 & 0.3017 & 0.2196 & 0.3541 \end{bmatrix}.$$

Similarly, the low-dimensional embedding of each first level indicators can be calculated as:

$$\bar{Y}_{c_1} = \left[0.4105 \quad 0.3619 \quad 0.3064 \quad 0.1927\right],$$

$$\bar{Y}_{c_2} = \left[0.2429 \quad 0.2667 \quad 0.3613 \quad 0.1857\right],$$

$$\bar{Y}_{c_3} = \left[0.3542 \quad 0.3118 \quad 0.2736\right],$$

$$\bar{Y}_{c_4} = \left[0.2631 \quad 0.2933 \quad 0.3217 \quad 0.1980\right],$$

$$\bar{Y}_{c_5} = \left[0.3691 \quad 0.2597 \quad 0.3032 \quad 0.2156\right]\cdot$$

The results show that Resource Structure has the greatest impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Member Reputation > Member R&D Capabilities > Member Innovation Resources > Member Cooperation experience. Contract Governance Mechanism ranked second in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Resource Sharing Mechanism > Cost Sharing Mechanism > Income Distribution Mechanism > Implementation Mechanism. Platform Openness ranked third in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Restrictive Conditions for Joining > Restrictions on the Utilization of Platform Resources > Restrictions on the Service Provision. Trust Level ranked fourth in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Service Levels > Information Sharing > Cooperation Relationship > Communication Status. Policy Environment ranked fifth in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Taxation System > Laws and Regulations System > Intellectual Property Protection System > Research Support Policy.

(2) Use sum product method to calculate the judgment matrix A of the primary indicators and the judgment matrix A_i of the secondary indicators.

Based on sum product method, obtain the weight vector of judgment matrix A: $W = \left[0.6422 \ \ 0.2116 \ \ 0.1995 \ \ 0.1834 \ \ 0.1422\right]$, and because $CR = 0.1547 > 0.1$, it is necessary to adjust A. Using the method proposed by Nefeslioglu (2013), obtain the adjusted judgment matrix A_1:

$$A_1 = \begin{bmatrix} 1 & 1/3 & 5 & 1/3 & 1/3 \\ 3 & 1 & 3 & 1/3 & 1/3 \\ 1/5 & 1/3 & 1 & 5 & 1/5 \\ 1/3 & 1/3 & 3 & 1 & 3 \\ 3 & 1/3 & 5 & 1/3 & 1 \end{bmatrix}.$$

The weight vector $W=\begin{bmatrix}0.2243 & 0.5032 & 0.4811 & 0.3898 & 0.6609\end{bmatrix}$ corresponding to judgment matrix A_1, and $CR=0.0251<0.1$.Similarly, the weight vector corresponding to judgment matrix A_{c_i} of each first level indicators can be calculated as:

$$W_{C_1}=\begin{bmatrix}0.4125 & 0.3992 & 0.3014 & 0.2833\end{bmatrix}(CR=0.0392<0.1),$$

$$W_{C_2}=\begin{bmatrix}0.3902 & 0.3018 & 0.2875 & 0.2614\end{bmatrix}(CR=0.0351<0.1),$$

$$W_{C_3}=\begin{bmatrix}0.2544 & 0.2043 & 0.1986\end{bmatrix} \quad (CR=0.0266<0.1),$$

$$W_{C_4}=\begin{bmatrix}0.3552 & 0.3098 & 0.2933 & 0.2412\end{bmatrix}(CR=0.0298<0.1),$$

$$W_{C_5}=\begin{bmatrix}0.3422 & 0.2794 & 0.2001 & 0.1934\end{bmatrix}(CR=0.0232<0.1).$$

The results show that Contract Governance Mechanism has the greatest impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Resource Sharing Mechanism > Income Distribution Mechanism > Cost Sharing Mechanism > Implementation Mechanism. Trust Level ranked second in impact on platform performance;. The ranking of factors affecting platform performance in this dimension is: Cooperation Relationship > Information Sharing > Service Levels > Communication status. Platform Openness ranked third in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Restrictive Conditions for Joining > Restrictions on the Utilization of Platform Resources > Restrictions on the Service Provision. Policy Environment ranked fourth in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Taxation System > Laws and Regulations System > Intellectual Property Protection System > Research Support Policy. Resource Structure has the smallest impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Member Reputation > Member R&D Capabilities > Member Innovation Resources > Member Cooperation Experience.

(3) Use the deviation matrix method to calculate the judgment matrix A of the primary indicators and the judgment matrix A_i of the secondary indicators:

Based on the deviation matrix method, obtain the weight vector of judgment matrix $A:W=\begin{bmatrix}0.6417 & 0.2254 & 0.2032 & 0.1965 & 0.1531\end{bmatrix}$, and because $CR=0.1631>0.1$, it is necessary to adjust A. The normalized matrix

A, the deviation matrix $|D|$, and the adjusted judgment matrix A_1 are obtained as follows:

$$A' = \begin{bmatrix} 0.6541 & 0.4954 & 0.7176 & 0.5356 & 0.5552 \\ 0.4221 & 0.3262 & 0.5183 & 0.3122 & 0.3705 \\ 0.3154 & 0.4937 & 0.4069 & 0.6448 & 0.4281 \\ 0.3013 & 0.5552 & 0.3788 & 0.3229 & 0.3104 \\ 0.2117 & 0.8913 & 0.3720 & 0.2134 & 0.6482 \end{bmatrix},$$

$$|D| = \begin{bmatrix} 0.0597 & 0.2413 & 0.1242 & 0.0478 & 0.2598 \\ 0.0333 & 0.3012 & 0.1402 & 0.3285 & 0.2972 \\ 0.0697 & 0.3905 & 0.4617 & 0.1496 & 0.2216 \\ 0.4932 & 0.3518 & 0.1865 & 0.1351 & 0.1943 \\ 0.2038 & 0.4779 & 0.3014 & 0.2105 & 0.4495 \end{bmatrix},$$

$$A_1 = \begin{bmatrix} 1 & 1/3 & 5 & 1/3 & 1/3 \\ 3 & 1 & 3 & 1/3 & 1/3 \\ 1/5 & 1/3 & 1 & 5 & 1/5 \\ 1/3 & 1/3 & 3 & 1 & 3 \\ 3 & 1/3 & 5 & 1/3 & 1 \end{bmatrix}.$$

The weight vector corresponding to A_1 is

$W = [0.5548 \quad 0.4974 \quad 0.4423 \quad 0.3185 \quad 0.2638] \, (CR = 0.0266 < 0.1)$.

Similarly, the weight vector corresponding to the judgment matrix A_{c_i} of each first level indicators can be calculated as:

$$W_{C_1} = [0.3934 \quad 0.3725 \quad 0.2509 \quad 0.2215] \, (CR = 0.0327 < 0.1),$$

$$W_{C_2} = [0.3502 \quad 0.2976 \quad 0.2793 \quad 0.2075] \, (CR = 0.0284 < 0.1),$$

$$W_{C_3} = [0.3592 \quad 0.2311 \quad 0.1995] \qquad (CR = 0.0279 < 0.1),$$

$$W_{C_4} = [0.2597 \quad 0.2296 \quad 0.1994 \quad 0.1682] \, (CR = 0.0369 < 0.1).$$

$$W_{C_5} = [0.3591 \quad 0.3277 \quad 0.2898 \quad 0.2620] \, (CR = 0.0279 < 0.1).$$

The results show that Resource Structure has the greatest impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Member Reputation > Member R&D Capabilities > Member Innovation Resources > Member Cooperation Experience. Trust Level ranked second in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Cooperation Relationship > Information Sharing > Service Levels > Communication Status. Platform Openness ranked third in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Restrictive Conditions for Joining > Restrictions on the Utilization of Platform Resources > Restrictions on the Service Provision. Policy Environment ranked fourth in impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Intellectual Property Protection System > Laws and Regulations System > Taxation System > Research Support Policy. Contract Governance Mechanism has the smallest impact on platform performance. The ranking of factors affecting platform performance in this dimension is: Resource Sharing Mechanism > Income Distribution Mechanism > Cost Sharing Mechanism > Implementation Mechanism.

4.2. Comparative analysis

Obviously, with the above three comparison methods, the new judgment matrix A_1 obtained through adjusting judgment matrix A needs to satisfy all the consistency conditions. In the new judgment matrix A_1 some element values have undergone major changes, such as a_{24} from the original 3 to 1/3, a_{34} from the original 1/5 to 5. This means, for instance, that the relationship between the second indicator and the fourth indicator, the importance of the former is considered to be three times more than the latter in the judgment matrix A, but after adjustment, the importance of the latter is three times more than the former. The original relationship between some of the elements was completely negated, and this adjustment was obviously unreasonable.

In addition, in order to compare the degree of weight change for each ranking method before and after the adjustment, the author proposes the weight adjustment range:

$$\textit{weight adjustment range} = \frac{\left|\text{Adjusted weight value-Preadjustment weight}\right|}{\text{Preadjustment weight}} \times 100\%. \tag{6}$$

According to formula (6), in the three ranking methods, the weight adjustment ranges of the second index are 65.57%, 73.96%, 57.24%, 69.92%, and 30.85% respectively; the weight adjustment ranges of the third indicator were 54.25%, 41.98%, 62.85%, 32.78% and 22.43% respectively. The average of all the adjustment range all reaches 50%, which is a large-scale adjustment for the weight value in the 0-1 range. Moreover, the ranking results of three methods have also been greatly changed. The ranking results between the second indexes and the fourth indexes in the original judgment matrix A illustrate that the contribution of trust level to platform performance is larger than that of policy environment. Yet after adjustment, it is considered that the contribution of policy environment to platform performance is larger than that of the trust level. It can be considered, unless it is in the initial construction of the judgment matrix, that the experts have made a serious error in judging the weight relationship between the indicators, otherwise the adjustment of judgment matrix is difficult to accept.

The method proposed in this paper uses the weight ratio as a measure of the coordinate value of the program in the evaluation system. It can effectively sort the non-conformance judgment matrix without the need to adjust the original judgment matrix and provide a theoretical basis for future performance improvement. The algorithm in this paper can retain the expert's original intention completely and make the sorting result more consistent with the objective reality. In addition, because of avoiding the consistency test, the computational complexity of this method has been significantly improved compared to the traditional AHP. The running time of the algorithm is shown in Table 3.

Table 3

Algorithm running time

Judgment matrix	Improved AHP and manifold learning model	Sum product method	Deviation matrix method
A	1	6.3	6.4

Time unit: s

Source: own figure.

According to the above analysis, when the judgment matrix is a non-uniform judgment matrix, the improved AHP and manifold learning model can not only reflect the objective sequence of the program (i.e. satisfy the order-preserving requirement) effectively, but also has low time complexity.

CONCLUSION

The key point to sorting non-conformance judgment matrix is to make full use of the existing discriminant information to achieve a reasonable evaluation, but most existing methods for adjusting the non-uniform judgment matrix generally focus on whether the adjusted judgment matrix satisfies the conformance requirement, and adjust the element in more arbitrary way while ignoring the original information effective retention.

This paper innovatively proposes an improved AHP method. Firstly, it analyzed the influence of the non-consistent judgment matrix on the AHP method. Then low-dimensional embedding was introduced and a new judgment matrix sorting process constructed. Finally, a kind of non-consistent judgment matrix sorting method based on the manifold learning was proposed.

Finally, this paper used the improved AHP method to carry out an empirical analysis for the performance evaluation of R&D and the transformation functional platform. The comparative analysis shows that, compared with the traditional AHP method, the improved AHP model can fully reflect experts' evaluation opinions. It can also provide a ranking conclusion that is more in line with the functional platforms of R&D and transformation within a relatively short time, which make the evaluation results more accurate and reliable.

REFERENCES

Acs, Z. J, Szerb, L., *Entrepreneurship, economic growth and public policy*, "Small Business Economics", 28(2), pp. 45-51, 2007.

Benitez, J., Delgado-Galvan, X., Izquierdo, J., Pérez-García, R., *Achieving matrix consistency in AHP through linearization*, "Applied Mathematical Modelling", 35(9), pp. 4449-4457, 2011.

Bidgoly, A. J., Ladani, B. T., *Modelling and Quantitative Verification of Reputation Systems Against Malicious Attackers*, "The Computer Journal", 58(10), pp.2567-2582, 2015.

Boudreau, K., *Open Platform Strategies and Innovation: Granting Access versus Devolving Control*, "Management Science", 56(10), pp. 849-1872, 2010.

Bregler, C., Omohundro, S. M., *Nonlinear Manifold Learning for Visual Speech Recognition*. International Conference on Computer Vision,1995.

Calabrese, A., Costa, R., Menchini, T., *Using Fuzzy AHP to Manage Intellectual Capital Assets: An Application to the ICT Service Industry*, "Expert Systems with Applications", 40(9), pp. 3747-3755, 2013.

Chen, Y., Fan, Z. P., *Research on the Consistency and Related Problems of Linguistic Judgment Matrix*, "System Engineering Theory and Practice", 24(4), pp. 136-141, 2004.

Chesbrough, H. W., *Open Innovation: The New Imperative for Creating and Profiting from Technology*, "California Management Review", 3(3), pp. 33-58, 2003.

Cho, D. S., Moon, H. C., Kim, M. Y., *Characterizing international competitiveness in international business research: a MASI approach to national competitiveness*, "Research in International Business and Finance", 22(4), pp. 175-192, 2008.

Claesson, A., A, *Configurable Component Framework Supporting Platform-Based Product Development*, Ph. D. Thesis, pp. 1-21. Product and Production Development, Chalmers University of Technology, Gothenburg 2006.

Cooke, P., *From Clusters to Platform Policies in Regional Development*, "European Planning Studies", 20(8), pp. 1415-1424, 2012.

Crimimisi, A., Shotton, J., Konukoglu, E., *Decision forests: a unified framework for classification, regression, density estimation, manifold learning and semi-supervised learning*, "Foundations and Trends in Computer Graphics and Vision", 7(3), pp. 81-227, 2011.

Eisenmann, T. R., Parker, G., Van Alstyne, M., *Opening Platforms: How, When and Why*, Harvard Business School, 12, pp. 9-30, 2008.

Fan, Z., Jiang, Y., Xiao, S., *Consistency and properties of fuzzy judgment matrix*, "Control and decision", 16(1), pp. 69-71, 2001.

Fang Y. H., Wang, L. T., *Research on operation mechanism and evaluation index system of military civilian integration industry innovation platform,* "Information journal", 36 (12), pp. 198-206, 2017.

Gassmann, O., *Opening up the innovation process: towards an agenda*, "R&D Management", 36(3), pp. 18-27, 2006.

Gedell, S., Michaelis, M. T., Johannesson, H., *Integrated Model for Co-Development of Products and Production Systems – A Systems Theory Approach*, "The Journal of Concurrent Engineering: Research and Applications", 19(2), pp. 139-156, 2011.

Harmaakorpi, V. K., Pekkarinen. S. K., *Regional development platform analysis as a tool for regional innovation policy*, "European Planning Studies", 14(8), pp. 1085-1104, 2006.

Hernandez, G., Allen, J. K., Mistree, F., *Platform Design for Customizable Products as a Problem of Access in a Geometric Space*, "Engineering Optimization", 35(3), pp. 229-254, 2003.

Hu, Y., Wen, J. Q., Yan, Y., *Measuring the performance of knowledge resources using a value perspective: integrating BSC and ANP*, "Journal of Knowledge Management", 19(6), pp. 1250-1272, 2015.

Huang, S. M., *Construction of Industry-University-Research Cooperation Mechanism Based on Stakeholders*, "Heilongjiang Animal Science and Veterinary Medicine", (7), pp. 25-29, 2016.

Jonsson, S., *The impact of institutional impediments and information and knowledge exchange on SMEs' investments in international business relationships*, "International Business Review", 19(6), pp. 548-561, 2010.

Krukow, K., Nielsen. M., *From simulations to theorems: A position paper on research in the field of computational trust*, "International Conference on Formal Aspects in Security& Trust", 4691, pp. 96-111, 2006.

Liu, S., Zhang, Y., Yu, D. Y., *Consistency and ranking of triangular fuzzy number complementary judgment matrix modified by niche genetic algorithm,* "System engineering theory and practice", 31(3), pp. 522-529, 2011.

Luo, P. L., Yin, H. X., *Incentive framework for knowledge sharing based on benefit game model*, "R & D Management", 21(2), pp. 24-30, 2009.

Lusch, R. F., Brown, J. R., *Interdependency,contracting,and relational behavior in marketing channels,* "Journal of marketing", 60(4), pp. 19-38, 1996.

Makipaa, M., *Planning for Inter-Organizational Information Systems in Practice*, "Lecture Notes in Business Information Processing", 86, pp. 98-111, 2011.

Medema, S. G., *Public Choice and the Notion of Creative Communities*, "History of Political Economy", 43(1), pp. 225–246, 2011.

Nefeslioglu, H. A., Sezer, E. A., Gokceoglu, C., Ayas, Z., *A Modified Analytical Hierarchy Process (M-AHP) Approach for Decision Support Systems in Natural Hazard Assessments*, "Computersand Geosciences", 59, pp. 1-8, 2013.

Nogoorani, S. D., Jalili, R., *Uncertainty in Trust: A Risk-Aware Approach, International Journal of Uncertainty,* "Fuzziness and Knowledge-Based Systems", 24(5), pp. 703-737, 2016.

Pan, Z., Li, Y. S., *Trust in Strategic Alliance: An Empirical Study under Chinese Context*, "China Industrial Economics" , 20(4), pp. 44-54, 2008.

Pernilla, I., Ulrica, L., Ingela, B., *Taking a Holistic Perspective on Technical Communication and Lean*, "Quality Innovation Prosperirity-Kvalita Inovacia", 19(2), pp. 103-122, 2015.

Petrusson, U., Rosen, H., Thornblad, T., *Global Technology Markets: The Role of Open Intellectual Property Platforms*, "Review of Market Integration", 2(2), pp. 333-392, 2010.

Porter, M. E., *Competitive Advantage, Agglomeration Economics and Regional Policy*, "International Regional Science Review", 19(3), pp. 85-90, 1996.

Reece, S., Rogers, A., Roberts, S., *Evaluating multidimensional trust within a decentralised reputation system*. In Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems, pp. 1063–1070, 2007.

Rui, M. J., Chen, X. J., *Economic analysis of invisible knowledge sharing in companies*, "Journal of management", 4(3), pp. 71-74, 2007.

Saaty, T. L., *The Analysis Hierarchy Process*. McGraw-Hill, New York 1980.

Saaty, T. L, Vargas, L. G., *Uncertainty and rank order in the analytic hierarchy process*, "European Journal of Operational Research", 32(1), pp. 107-117, 1987.

Sabater, J., Sierra, C., *A reputation model based on social relations*, "ACM SIGecom Exchanges", 3(1), pp. 44-56, 2002.

Tang, W., Chen, Z., *Research on subjective trust management model based on fuzzy set theory*, "Journal of software",14(8), pp. 1401-1408, 2004.

Teacy, W. T. L., Luck, M., Rogers, A., Jennings, N. R. *An efficient and versatile approach to trust and reputation using hierarchical Bayesian modelling*, "Artificial Intelligence", 19(3), pp. 149–185, 2012.

Wang, X. X., *Risk factors assessment and countermeasures of slopes during high-grade highway operation*. Tongji University, 2008.

Wang, J., *Research and Realization on Decision Support System for Flood Control Consultation*. Harbin Engineering University, 2005.

Wei, C. P., Zhang, Y. Z., *Consistency checking and ranking method of interval number judgment matrix*, “Systems Engineering Theory and Practice”, 27(10), pp. 132-139, 2007.

Xia, H. X., Tan, Q. M., *Research on high-end new industrial innovation platform of equipment manufacturing industry,* “Scientific research management”, 38(12), pp. 1-10,2017.

Xu, D. H., Lv, X. Z., Yuan, W., Huang, Z., *Research on the performance evaluation index system of national science and technology infrastructure platforms' running service*, “China basic science”, (1), pp. 40-43, 2013.

Yu, J B., *Bearing performance degradation assessment using locality preserving projections*, “Expert Systems with Applications”, 38(6), pp. 7440-7450, 2011.

Zvolinschi, A., Kjelstrup, S., *An Indicator to Evaluate the Thermodynamic Maturity of Industrial Process Units in Industrial Ecology*, “Journal of Industrial Ecology”, 12(2), pp. 159-172, 2008.

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