

---

AI translation · View original & related papers at  
[chinaxiv.org/items/chinaxiv-202304.00486](https://chinaxiv.org/items/chinaxiv-202304.00486)

---

## Research on Expert Recusal Models for Research Projects Based on Co-authorship: Postprint

**Authors:** Dai Shiyu, Shi Jin, Li Ming

**Date:** 2023-04-01T16:02:56+00:00

### Abstract

[Purpose/Significance] Aiming at the recusal issues in the selection of review experts for research projects, this study attempts to propose a feasible modeling approach for identifying experts to be recused, so as to avoid interference from interpersonal relationships in the review process and ensure the standardization and fairness of scientific research evaluation. [Method/Process] First, taking the paper collaboration relationships between experts and applicants as the entry point, we employ collaboration intensity, co-author depth, research direction alignment, and review performance as the main indicators. Then, we analyze these indicators using comprehensive weights and a modified TOPSIS method to construct a quantitative model for expert recusal oriented toward research projects. Finally, based on the specified number of expert panel members and considering the distribution of age, institution, gender, and other factors, we identify the experts who should be recused. [Results/Conclusion] Testing shows that when generating the list of experts to be recused, this model can effectively avoid the problem of a “collaboration-only” bias, provides sufficient reasons for recusal, meets the requirements of science and technology management departments for expert selection, and can offer certain decision support for the expert selection process.

### Full Text

### Preamble

**Volume 65, Issue 18, September 2021**

### Research on Expert Avoidance Model for Scientific Research Projects Based on Paper Cooperation Relationships

Dai Shiyu, Shi Jin, Li Ming

School of Information Management, Nanjing University, Nanjing 210023

**Abstract:** [Purpose/Significance] Aiming at the avoidance problem in the selection of peer review experts for scientific research projects, this paper attempts to propose a set of feasible model methods to determine avoidance experts, avoid interference from interpersonal relationships in evaluation work, and ensure the standardization and fairness of scientific research evaluation. [Method/Process] First, taking the paper cooperation relationship between experts and applicants as the entry point, cooperation intensity, co-author depth, direction matching degree, and review performance are taken as the main indicators. Then, comprehensive weighting and modified TOPSIS method are used to analyze each indicator to construct a quantitative model for expert avoidance in scientific research projects. Finally, according to the specified number of expert group members and considering the distribution of age, institution, gender, etc., the experts who should be avoided are identified. [Result/Conclusion] Through testing, the model can effectively avoid the problem of “cooperation-only theory” when providing the list of avoidance experts, with sufficient reasons for avoidance, meeting the requirements of the Ministry of Science and Technology Management for expert selection, and can provide certain decision support for expert selection work.

**Keywords:** paper cooperation relationship; expert avoidance model; modified TOPSIS method; scientific research project

**Classification Number:** G250

**DOI:** 10.13266/j.issn.0252-3116.2021.18.013

Peer review is currently the universal academic evaluation method in the international academic community and the fundamental mechanism for scientific foundations to select innovative projects. It is often used in the evaluation of scientific research projects, research institutions, and professional titles. Peer review typically involves three main parties: review experts, those being evaluated, and scientific management institutions. Whether review experts can perform their duties scientifically and impartially affects the quality of peer review to a certain extent. To this end, research management departments often adopt avoidance systems to screen out review experts who have conflicts of interest with fund projects or those being evaluated, mainly in three forms: self-avoidance, application avoidance, and mandatory avoidance [1]. Due to the increasing frequency of disciplinary exchanges and the increasing refinement of research directions, blindly determining avoidance experts based on official regulations or social relationships may filter out “small peer” experts, creating an “excessive avoidance” problem. This may force the inclusion of experts unfamiliar with the discipline to meet the required number of panel members, thereby reducing the professionalism of peer review [4].

Given the above problems, this study takes expert selection in scientific research project evaluation as the research background. Based on the premise that preliminary expert screening has been completed, it starts from the paper cooperation relationship of review experts, comprehensively considers factors

such as cooperation intensity, research direction, and review performance, and uses the modified TOPSIS (technique for order preference by similarity to an ideal solution) method to construct a quantitative model for expert avoidance. This model can assist research management departments in better grasping the avoidance intensity, reasonably determining the candidates for avoidance experts, thereby optimizing the personnel structure of the review expert group and ensuring the objectivity and fairness of scientific research evaluation.

## 2 Related Work

### 2.1 Policy Research on Expert Avoidance

Foreign countries use “conflict of interest” (COI) to express the meaning of avoidance. To reduce the impact of COI on scientific research activities, many developed European and American countries have formulated guideline-based management policies, which can be roughly divided into two models: the American model and the British model [5]. At the same time, many scholars have conducted academic discussions around disclosure policies of academic institutions and journals. A. Nichols-Casebolt et al. [6] summarized current views on institutional conflicts of interest, believing that academic institutions must develop resolution strategies based on their own COI characteristics. To make COI better understood and valued, scholars such as N. H. Kong [7], C. Johnson [8], and A. J. Epstein [9] applied COI research specifically to the healthcare industry, discussing the nature, impact, and management measures of COI from the perspective of industry practitioners. J. Silva et al. [10] took editors as research subjects, exploring the impact of potential conflicts of interest brought by editors’ own relationship networks on their publication decisions, believing that editors should actively disclose their networks, positions, and resumes.

In contrast, domestic research on avoidance policies started relatively late. The “Science and Technology Evaluation Standards” promulgated in 2001 is the first normative guideline document for science and technology evaluation activities in China. It clarified the types of personnel to be avoided in the evaluation process and laid the foundation for the current peer review expert avoidance system [11]. The “Decision on Improving Science and Technology Evaluation Work” released in 2003 marked the formal appearance of the avoidance system in regulations, requiring strict implementation of avoidance systems and regular rotation of expert groups [12]. The “National Natural Science Foundation Regulations” [13] and the “National Social Science Fund Management Measures” [14] provide specific provisions for expert avoidance from multiple aspects including age, affiliation, social relationships, and research capabilities.

### 2.2 Model Research on Expert Avoidance

Since few foreign studies involve expert avoidance models, this section focuses on domestic model research results, mainly including theoretical frameworks and practical applications. At the theoretical framework level, Lei Xue et al. [15]

started from the extraction and mining of academic relationships, preliminarily explored the measurement approach to handling expert avoidance issues in peer review, and designed a prototype of an avoidance evaluation model accordingly, which has enlightening significance for proposing more specific and feasible avoidance measurement models in the future. Pan Yuntao et al. [4] and Wang Xianhui et al. [16] focused on experts' social relationships, assigned values to relationships according to closeness, set review thresholds according to different review requirements, and compared the two to determine avoidance experts.

In practical applications, Zhang Zhiqing et al. [2] used indicators such as shortest path distance and betweenness centrality to quantify the social network status of review experts, eliminating authoritative experts and “bridge” experts to complete avoidance. This study fully considered the impact of social relationships on expert review activities. Li Jiang et al. [17] proposed a social association value algorithm to quantify teacher-student relationships, colleague relationships, and cooperation relationships, determining whether experts need to avoid based on logical values, and used a self-constructed test dataset to verify the model's effectiveness.

Overall, current management policies on expert avoidance in scientific research project evaluation still have problems such as insufficiently detailed avoidance reasons and excessive reliance on expert self-awareness. Some designed expert avoidance models remain at the framework level with insufficient operational details, increasing the difficulty of practical use. Additionally, some studies have not clarified the specific scenarios of expert avoidance problems, and the degree of scenario refinement and differentiation awareness is not high. Therefore, this study attempts to design a quantitative model for expert avoidance applicable to scientific research project evaluation occasions for research management institutions. The model will comprehensively measure experts' cooperation relationships, professional capabilities, and personal qualities by constructing avoidance reference indicators focusing on cooperation intensity, co-author depth, direction matching degree, and review performance. Then, using comprehensive weighting and modified TOPSIS method, it will calculate the avoidance value of each expert. The higher the avoidance value, the more the expert should theoretically be avoided. Finally, based on the age, affiliation, and other restrictions in the expert management documents issued by science and technology management departments, combined with the given number of expert group members, the list of avoidance experts will be objectively and reasonably identified to ensure the fairness, professionalism, and democracy of the review process and promote the progress of scientific research evaluation.

### 3 Research Design

#### 3.1 Overall Framework

The research steps of this paper are as follows: Obtain Chinese and English cooperation papers of experts from CNKI and Web of Science, summarize co-authors, and judge whether there is a cooperation relationship between applicants and experts; Based on literature research, refer to the indicator systems proposed by predecessors for peer review expert selection, and combine with the characteristics of this study, taking cooperation intensity, co-author depth, review performance, and direction matching degree as the main indicators to quantify expert avoidance in scientific research project evaluation; Use combination weighting to set the weights of each indicator to reduce the impact of different attribute importance levels, and input each indicator value into the expert avoidance model based on modified TOPSIS method to obtain the theoretical avoidance value of each expert; Sort the theoretical avoidance values, comprehensively consider the requirements of science and technology management departments such as expert age and affiliation, and obtain the list of experts who should be avoided. The framework and process of the quantitative expert avoidance model from the perspective of paper cooperation relationships are shown in Figure 1 [Figure 1: see original paper].

#### 3.2 Reference Indicators and Quantification Methods

As known from the above research, expert avoidance problems are mostly analyzed from multiple relationships such as social relationships and academic relationships. However, many of these relationships are relatively obscure and difficult to define. Therefore, the relationships that can truly be included in the research discussion are those that are easy to extract and evaluate, such as paper cooperation relationships. However, if avoidance experts are selected solely based on paper cooperation relationships, it will create an “excessive avoidance” problem. In some relatively unpopular research fields, there may even be no experts available for selection. Therefore, it is necessary to consider other perspectives. In-depth research found that as early as the 1990s, many scholars had proposed a series of indicators for expert selection in peer review, jointly with the National Natural Science Foundation Committee. These can be summarized as social attributes, moral cultivation, academic level, review performance, research activity, and work attitude, and experts are comprehensively evaluated based on these [18-20]. In addition, mainstream research institutions worldwide (Chinese Academy of Sciences, National Institute of Standards and Technology, etc.) often use academic ability, review experience, conflict of interest, etc. as the basis for selecting experts [21]. Based on this, this study decides to take paper cooperation relationships as the entry point, and following principles of systematicity, scientificity, and typicality, takes cooperation intensity, direction matching degree, and review performance as the main indicators to conduct quantitative research on expert avoidance in scientific research project evaluation. Each indicator will be explained in detail below and summarized in

Table 1 :

**Table 1 Expert Avoidance Indicators**

Indicator Type	Indicator Name	Nature
Cooperation Intensity	Cooperation Frequency	Cost-type
	Time Difference $\Delta T$	Cost-type
Co-author Depth	Co-author Depth	Cost-type
Review Performance	Review Reputation	Cost-type
	Consistency Degree	Benefit-type
	Deviation Degree	Cost-type
Direction Matching Degree	Direction Matching Degree	Benefit-type

**3.2.1 Cooperation Intensity** If an expert has cooperated with an applicant, this only indicates that the expert is more familiar with the applicant than with other applicants. However, familiarity does not mean favoritism. It is also necessary to observe the expert's moral quality and review experience, but such information is generally kept by science and technology management departments and usually cannot be obtained. This is also why the model proposed in this study is only oriented toward research management departments. Cooperation intensity reflects the strength of the paper cooperation relationship between experts and applicants, not the expert's own cooperation ability level. Research in this area mainly focuses on regional cooperation intensity, industry-university-research cooperation intensity, etc. Quantitative research on cooperation intensity between scholars is relatively scarce, with more focus on studying potential cooperation relationships and cooperation network visualization to measure and predict scholars' cooperation abilities. Based on this situation, this study attempts to measure cooperation intensity using two factors: cooperation frequency and time difference.

**(1) Cooperation Frequency  $S_{ep}$ .** Cooperation frequency refers to the number of papers co-authored by experts and applicants. Considering that the value of cooperation frequency is generally large, to facilitate subsequent data processing and avoid natural weight problems, this study borrows the method proposed by G. Salton for measuring cooperation between two parties, namely the Salton index [22], to normalize the cooperation frequency. The specific calculation formula is as follows:

$$S_{ep} = \frac{a_{ep}}{\sqrt{a_e \times a_p}} \quad (\text{Formula 1})$$

In Formula (1),  $a_{ep}$  is the number of cooperation papers between the expert and the applicant,  $a_e$  refers to the total number of cooperation papers of the expert, and  $a_p$  refers to the total number of cooperation papers of the applicant.

Generally, the higher the Salton index between the expert and the applicant, the more frequent their cooperation.

**(2) Time Difference  $\Delta T$ .** Time difference refers to the difference between the current year and the publication year of the most recent cooperation paper between the expert and the applicant. Currently, there is little research on the impact of time difference on the closeness of cooperation relationships, but this does not mean that time difference has no impact on cooperation relationships. Therefore, this study assumes that the time difference between the two parties has a negative impact on the closeness of the cooperation relationship; that is, the larger the time difference value, the smaller the cooperation intensity between the expert and the applicant.

**3.2.2 Co-author Depth** Currently, more and more scholars choose to cooperate with others to conduct scientific research. As the number of co-authors increases, the relationship strength between a scholar and each co-author theoretically decreases. Specifically, for the same research, suppose scholar A has two cooperation situations: only cooperating with B; cooperating with B and C. When problems arise, in the former case, A will only discuss with B, while in the latter case, A can also contact C, meaning that to a certain extent, C weakens the cooperation relationship between A and B. In addition, Chen Yunwei et al. [23] found through analyzing experts' cooperation structures that cooperation relationships may need to be comprehensively analyzed from multiple perspectives such as the source institutions of co-authors, the proportion of cooperation papers, and co-author depth. Therefore, this study introduces the indicator of co-author depth based on existing indicators. It refers to the average number of co-authors per paper. The smaller the co-author depth value, the closer the cooperation relationship between the expert and the applicant.

**3.2.3 Review Performance** Review performance can reflect an expert's work level and work attitude. Here, this study refers to the review expert credit evaluation indicator system proposed by He Xiaoyu [24], selecting consistency degree and deviation degree as calculation indicators for review quality. Among them, consistency degree refers to the degree of consistency between an expert's evaluation results for applied projects and the final evaluation results, which has a positive impact on review quality. Deviation degree includes horizontal deviation degree and vertical deviation degree, that is, the difference between an expert's review results and other experts' results in the same project, and the fluctuation degree compared with the expert's historical review results, which has a negative impact on review quality. It should be noted that project review results are generally at three levels: A, B, and C. For ease of quantification, they are replaced with 5, 3, and 1. The specific calculation formulas are as follows:

**Consistency Degree  $A_i$ :**

$$A_i = \frac{p}{m} \quad (\text{Formula 2})$$

**Deviation Degree  $B_i$ :**

$$B_i = \frac{\sum_{j=1}^m (x_{ij} - \bar{x}_j)^2}{\sum_{j=1}^m (x_{ij} - \bar{x}_i)^2 + \sum_m} \quad (\text{Formula 3})$$

In Formula (2),  $p$  represents the number of projects recommended by the expert that are consistent with those recommended by the expert group, and  $m$  represents the number of projects reviewed by expert  $i$ . In Formula (3),  $x_{ij}$  represents the review result of expert  $i$  for project  $j$ ,  $\bar{x}_i$  represents the average value of expert  $i$ 's participation in review results, and  $\bar{x}_j$  represents the average value of all experts' review results for project  $j$ .

**3.2.4 Direction Matching Degree** This study attempts to use direction matching degree to measure experts' research directions and judge whether they are big peers, small peers, or even laymen. It is simplified from the "expertise matching degree" indicator proposed by Li Jiang et al. [17] when discussing expert recommendation models, referring to the matching degree between the expert's research direction and the review project theme. The expert's research direction is mainly understood through personal homepage introductions and keyword frequency in recent papers. The review project theme can be obtained from the keywords in the project application and official document introductions. Then, the keywords of the expert's research achievements are compared with the project keywords, and the matching times  $n_k$  of each keyword are counted. Due to the time lag in research publication, experts may have new research directions during this period. Therefore, the negative impact of lag on direction matching degree should be considered in the calculation. The specific calculation formula is as follows:

$$M = \sum_{k=1}^a (t_k \times n_k) \quad (\text{Formula 4})$$

In Formula (4),  $a$  is the number of keywords of the research project,  $t_k$  is the time lag indicator of the  $k$ th matching keyword,  $t_k = e^{-\Delta t}$ , where  $\Delta t$  is the difference between the year of the most recent appearance of the matching keyword and the current year. It is set that  $M > 1$  indicates a small peer expert, and  $M \in (0, 1)$  indicates a big peer expert.

### 3.3 Weight Setting

Currently, weight determination methods can be roughly divided into subjective weighting methods and objective weighting methods. Subjective weighting methods can better reflect the real situation of evaluation indicators but have human interference. Objective weighting methods are data-based and scientific but ignore the internal connections of indicators, change with sample size, and have poorer stability, inheritability, and interpretability than subjective weighting.

Both methods have information loss problems. Therefore, this study selects the expert evaluation method and entropy weight method, using Euclidean distance function to calculate combination weights for each indicator.

**3.3.1 Expert Evaluation Method** Invite teachers with review experience, scholars with project application experience, and researchers familiar with the method to form a scoring group to score the importance of each indicator, with a score range of (0, 1). The final subjective weight calculation formula for each indicator is as follows:

$$Q_j = \frac{\sum_{i=1}^{h_j} C_{ij}}{\sum_{j=1}^n \sum_{i=1}^{h_j} C_{ij}} \quad (\text{Formula 5})$$

In Formula (5),  $h_j$  refers to the number of people scoring indicator  $j$ , and  $C_{ij}$  refers to the score of group member  $i$  for indicator  $j$ .

**3.3.2 Entropy Weight Method** According to the indicator properties in Table 1, the relevant data are standardized. The specific steps are as follows:

(1) **Data Standardization.** The processing formulas are as follows:

For benefit-type indicator  $j$ :

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (\text{Formula 6})$$

For cost-type indicator  $j$ :

$$r_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \quad (\text{Formula 6})$$

In Formula (6),  $x_{ij}$  represents the value of the  $j$ th indicator of the  $i$ th expert,  $x_j^{\min}$  refers to the minimum value of the  $j$ th indicator,  $x_j^{\max}$  refers to the maximum value of the  $j$ th indicator,  $m$  is the number of candidate experts who have paper cooperation relationships with the applicant, and  $n$  is the number of indicators.

(2) **Calculate Entropy Value  $e_j$ :**

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij}, \quad p_{ij} = \frac{r_{ij} + 10^{-4}}{\sum_{i=1}^m (r_{ij} + 10^{-4})} \quad (\text{Formula 7})$$

(3) **Calculate Objective Weight  $w_j$ :**

$$w_j = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)}, \quad w_j \in [0, 1], \quad \sum_{j=1}^n w_j = 1 \quad (\text{Formula 8})$$

**3.3.3 Comprehensive Weight  $W_j$**  He Xiaoyu [24] believes that by using Euclidean distance function, the preference coefficients of subjective and objective weights can be calculated, and then the comprehensive weight of each indicator can be obtained. This can combine the measurement advantages of subjective and objective weighting methods, making the weight value more objectively and reasonably reflect the importance of indicators in the system. The specific steps are as follows:

(1) Calculate Preference Coefficients  $\alpha$  and  $\beta$ :

$$D(Q_j, w_j) = \sqrt{\sum_{j=1}^n (Q_j - w_j)^2}, \quad D(Q_j, w_j)^2 = (\alpha - \beta)^2, \quad \alpha + \beta = 1 \quad (\text{Formula 9})$$

(2) Calculate Comprehensive Weight  $W_j$ :

$$W_j = \alpha Q_j + \beta w_j \quad (\text{Formula 10})$$

### 3.4 Expert Avoidance Model Algorithm

This study attempts to use the modified TOPSIS method as the model algorithm to determine the list of avoidance experts. By fixing the negative ideal solution at the origin and making the minimum value half of the maximum value after data standardization, it effectively solves the ranking reversal problem and self-contradiction problem existing in the traditional TOPSIS method, achieving algorithm optimization [25]. The reason for choosing this algorithm is mainly that the original purpose of this study is to find a reference point, calculate its relative distance from the expert's avoidance value, and the smaller the distance, the more the expert should be avoided, and then find the relatively more avoidable expert. The basic principle of TOPSIS method happens to coincide with this.

The specific algorithm steps are as follows:

(1) Standardize the original data and construct the indicator matrix  $(Z_{ij})_{m \times n}$ . The processing formulas are:

For benefit-type indicators:

$$Z_{ij} = 0.5 \times \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (\text{Formula 11})$$

For cost-type indicators:

$$Z_{ij} = 0.5 \times \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \quad (\text{Formula 11})$$

(2) Construct the weighted decision matrix  $(Y_{ij})_{m \times n}$ :

$$Y = (Y_{ij})_{m \times n} = W_j \cdot Z_{ij} \quad (\text{Formula 12})$$

(3) Determine the positive and negative ideal solutions  $Y^+$  and  $Y^-$ :

$$Y^+ = (1, 1, \dots, 1), \quad Y^- = (0, 0, \dots, 0) \quad (\text{Formula 13})$$

(4) Use Euclidean distance function to calculate the distance  $d_i^+$  and  $d_i^-$  between each indicator and the ideal solution:

$$d_i^+ = \sqrt{\sum_{j=1}^n (Y_{ij} - 1)^2}, \quad d_i^- = \sqrt{\sum_{j=1}^n (Y_{ij} - 0)^2} \quad (\text{Formula 14})$$

(5) Calculate the relative closeness  $K_i$ :

$$K_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (\text{Formula 15})$$

In Formula (15),  $K_i$  represents the closeness between expert  $i$ 's avoidance situation and the avoidance reference point (absolute ideal solution). Theoretically, the larger  $K_i$ , the more expert  $i$  should be avoided.

After the above process, the  $K_i$  values of all experts need to be sorted in descending order to clearly reflect their theoretical avoidance values. Then, using the officially given number of expert group members as a constraint, the list of experts who should theoretically be avoided can be obtained. However, considering that research management departments have certain restrictions on the gender distribution, age, and affiliations of expert group members, these factors should also be considered based on the sorting results to make the member structure of the expert group more reasonable.

## 4 Algorithm Testing

### 4.1 Model Testing

First, based on the list of major project review experts published by the Management Science Department of the National Natural Science Foundation, 19 experts were randomly selected as the candidate expert sample set. Then, given that the research is based on paper cooperation relationships, the co-authors of each expert in 2010-2020 were collected and placed in Excel's random extractor. If the extraction result was a foreign name or did not meet the applicant requirements of the National Natural Science Foundation, it was re-extracted. Finally, 15 potential applicants were randomly generated (this is an operation to construct the test sample set; research management institutions do not need to obtain applicants this way in actual use). Next, the publication status of experts and applicants in 2010-2020, including the number of papers, publication time, and keywords, was collected from CNKI and Web of Science databases to observe the paper cooperation between experts and applicants. It was found that 4 experts had no paper cooperation with applicants. To simplify the analysis process, they were temporarily regarded as review experts, but in actual

use, their social relationships and other cooperation forms need to be further considered. Finally, starting from the paper cooperation relationships between the remaining 15 candidate experts and applicants, the application of the above model in discussing expert avoidance situations was illustrated.

**(1) Calculate initial indicator values.** According to the model indicator quantification method in Section 3.3, the existing data of experts and applicants were calculated to obtain the initial indicator values (see Table 2 ). It should be noted that this study uses random assignment to obtain some relatively unavailable data. Taking deviation degree as an example: experts generally present review results in the form of A, B, and C. For calculation convenience, they are replaced with 5, 3, and 1. Then, for each expert, array [5, 3, 1] is randomly assigned 5 times, and the random data are processed according to the calculation formula to obtain the deviation degree required for the test model. Although this may cause deviations in the testing process, for internal personnel of research management institutions who can obtain these data, the probability of deviation will be greatly reduced, so this problem will not affect the actual use of the model.

**(2) Calculate subjective weights using the expert evaluation method.** Ten experts were invited to independently score each indicator. After multiple rounds of feedback and modification, the subjective weights of indicators were determined according to Formula (5) as  $Q_j = (0.242, 0.140, 0.138, 0.143, 0.087, 0.153, 0.102)$ .

**(3) Calculate objective weights using the entropy weight method.** First, Formula (6) was used to standardize the initial values of each indicator. Then, according to Formulas (7)-(9), the objective weights of each indicator were calculated (see Table 3 ).

**(4) Calculate comprehensive weights.** Now that the subjective and objective weights of each indicator have been obtained, they are substituted into Formula (9) to calculate the preference coefficients of subjective and objective weights, obtaining  $\alpha = 0.614$  and  $\beta = 0.386$ . Then, according to Formula (10), the comprehensive weights of each indicator can be obtained, as shown in Table 4 .

**(5) Based on the modified TOPSIS method given in Section 3.5, the standardized indicators are corrected to construct the final standardized matrix.** On this basis, the weighted decision matrix is obtained by combining comprehensive weights. Then, according to Formulas (14) and (15), the Euclidean distances from candidate experts to the positive and negative ideal solutions and the relative closeness are calculated. The relative closeness is the theoretical avoidance value given by the model designed in this study. Finally, the theoretical avoidance values of each expert are sorted. The larger the theoretical avoidance value, the more the expert should be avoided. The specific results are shown in Table 5 .

Assuming that the officially given number of review expert group members is 11,

and there are already 4 members, then according to the sorting results in Table 5, the experts who should theoretically be avoided are  $e_{14}, e_8, e_6, e_9, e_{15}, e_5, e_{12}, e_{10}$ .

#### 4.2 Result Analysis

From the above, the review expert group members of this project are  $e_1, e_2, e_3, e_7, e_{11}, e_4, e_{13}$ , and 4 experts who have no paper cooperation relationship with the applicants. The following analysis and verification of the expert group are conducted.

Regarding the basic situation of the review expert group, according to some requirements of science and technology management departments for the composition of expert group members, such as a certain proportion of young and female scientific and technical personnel, and a limit of 1 member from the same legal entity, the age, affiliation, and other attribute characteristics of expert group members are analyzed. Specifically, by browsing the personal homepages of review expert group members and observing their age, gender, affiliation, and years of participating in evaluation, it was found that the average age of expert group members is 53 years old, most come from different research institutions and universities, the consecutive years of participation do not exceed two years, and there are 3 female experts and 3 young researchers, meeting official requirements. Then, their direction matching degree was observed, finding 1 big peer expert and 6 small peer experts. For the 4 experts without cooperation, their research fields on their homepages were observed, and 1 was found to be consistent with the project theme. Therefore, there are 7 small peer experts in total, accounting for 63.6%, avoiding the problem of review results being far off due to too high a proportion of big peer experts. It can be seen that the composition of expert group members obtained using the model proposed in this study is relatively reasonable.

After clarifying the nature of expert group composition, a comparative analysis of avoidance experts and review experts was conducted. The results show that the basic situation of  $e_{12}$  is similar to that of  $e_7$  and  $e_4$ , and the research direction is more consistent, but it is required to be avoided due to excessive deviation degree. This shows that experts with similar cooperation degrees in the model do not necessarily all need to be avoided. The situations of the pairs  $e_1$  and  $e_{10}$ , and  $e_2$  and  $e_{14}$  are very similar, that is, the direction matching degree of each pair is similar, and the latter's cooperation degree is higher than the former's. In terms of project familiarity alone, the latter is relatively more suitable. However, considering their review performance, the latter's personal reputation and review quality are slightly inferior, so the latter is included in the avoidance list. In addition, from the avoidance list given by the model, although most avoidance experts have high cooperation intensity, there are also experts such as  $e_{12}$  and  $e_6$  who are not closely cooperating with applicants but are required to be avoided for other reasons, indicating that the avoidance process in this model indeed does not follow "cooperation-only theory."

Finally, some seemingly unreasonable situations in the results are explained.  $e_5, e_8, e_{15}$  are the three experts among the 15 who have the closest cooperation relationship with the applicants, and their direction matching degree is also relatively high, indicating they are very familiar with the project research field. Logically, they should be retained. However,  $e_5$  and  $e_8$  have low reputation, and  $e_5$  and  $e_{15}$  have large deviation degrees in their review results, showing a tendency for interpersonal relationships to interfere with review. Therefore, this model defines them as avoidance experts. The direction matching degree of  $e_6$  is almost 0, but it has just started cooperating with the applicant. This phenomenon seems unreasonable. The author believes that it may be because this expert started research in the project-related field earlier but is currently breaking through new directions. Therefore, it may be considered that the expert's grasp of the development trend and current hotspots of the project research theme is not precise enough, so it is avoided. In summary, the model proposed in this study has sufficient and reasonable reasons for avoidance when determining avoidance experts, and the composition of expert group members meets actual needs. It can assist science and technology management departments in expert selection work, reduce the workload of research management departments, and provide reference for automating expert avoidance operations.

Compared with existing models on expert avoidance in scientific research projects, the model proposed in this study has the following advantages:

1. **More comprehensive indicator selection.** Indicators are set from three aspects: experts' cooperation situation, professional level, and personal cultivation to comprehensively measure the adaptability between experts and scientific research review projects, rather than focusing only on experts' social attributes and selecting experts based on whether there is a relationship or the relationship strength.
2. **More scientific quantification method.** The importance of each avoidance indicator is determined based on subjective and objective weights, which can reduce the error of avoidance values to a certain extent. In addition, the TOPSIS comprehensive evaluation method is used as the basic algorithm of the model. This method is suitable for internal sorting of sample data and is the easiest to implement among commonly used evaluation algorithms. Compared with newly designed algorithms, it is also more mature and reliable.
3. **More specific operational process.** It no longer stays at the extraction approaches of various relationships in avoidance problems and the architecture of conceptual models. It clearly elaborates the quantification method of cooperation relationships and the use process of the avoidance model, and attempts to use test sample sets to verify the model effect.
4. **Clearer applicable objects.** Designed for research management institutions, applicable to scientific research project evaluation occasions, focusing on how to reasonably determine avoidance experts when there are

paper cooperation relationships between experts and applicants.

Of course, this study also has limitations. For example, due to the unavailability of review performance and applicant data, random assignment/extraction is used. The results obtained in this way have certain deviations compared with those obtained using first-hand data. However, this problem is relative because internal personnel of research management institutions can relatively easily obtain the above data, so theoretically it will not affect the use of the model. In addition, the current study is only based on paper cooperation data of review experts. Future research will consider other cooperation forms such as project cooperation and book co-authorship, and further expand the sample data size. The research scenario will no longer be limited to scientific research project evaluation but will extend to broader spaces, laying the foundation for developing an avoidance model with scenario universality.

## References

- [1] Zhang Qi. Research on the Avoidance System of Academic Evaluation [D]. Shanghai: Fudan University, 2008.
- [2] Zhang Zhiqing, Fan Yan, Su Shunhua. Research on Selection and Avoidance Strategy of Scientific Research Project Review Experts Based on SNA [J]. Journal of Wuhan University of Technology (Information & Management Engineering), 2016, 38(3): 367-371.
- [3] Zhu Weizhu, Li Chunfa. Empirical Research on “Small Peer” Review Expert Selection Method Based on Conceptual Knowledge Network [J]. Journal of Intelligence, 2017, 36(7): 78-83, 88.
- [4] Pan Yuntao, Su Cheng, Zhao Xiaoyuan, et al. Research on Technical Framework of Expert Identification and Recommendation Module [J]. Journal of the China Society for Scientific and Technical Information, 2016, 35(9): 923-931.
- [5] Wei Yidong. British and American Management Models of Conflict of Interest in Scientific Activities and Their Enlightenment [J]. Science and Society, 2017, 7(2): 70-85.
- [6] Nichols-Casebolt A, Macrina F L. Current perspectives regarding institutional conflict of interest: commentary on “institutional conflicts of interest in academic research” [J]. Science and engineering ethics, 2019, 25(6): 1671-1677.
- [7] Kong N H, Chow P K. Conflict of interest in research-the clinician scientist’s perspective [J]. Annals of the Academy of Medicine, Singapore, 2013, 42(11): 623-628.
- [8] Johnson C. Conflict of interest in scientific publications: a historical review and update [J]. Journal of manipulative and physiological therapeutics, 2010, 33(2): 81-86.
- [9] Epstein A J, Busch S H, Busch A B, et al. Does exposure to conflict of

interest policies in psychiatry residency affect antidepressant prescribing? [J]. *Medical care*, 2013, 51(2): 199-203.

[10] Silva J, Dobranszki J, Hollar, et al. Editors should declare conflicts of interest [J]. *Journal of bioethical inquiry*, 2019, 16(2): 279-298.

[11] Li Xin. *Research on Expert Avoidance System for Science and Technology Evaluation* [D]. Beijing: Institute of Scientific and Technical Information of China, 2015.

[12] Li Xing. *Research on Expert Avoidance System for Science and Technology Evaluation* [D]. Beijing: Institute of Scientific and Technical Information of China, 2015.

[13] National Natural Science Foundation of China. Regulations of the National Natural Science Foundation [EB/OL]. [2021-08-18]. <http://www.nsf.gov.cn/publish/portal0/tab471/info70222>

[14] National Office for Philosophy and Social Sciences. Management Measures of the National Social Science Fund [EB/OL]. [2021-06-03]. <http://www.nopss.gov.cn/n/2013/0520/c219644-21542088.html>.

[15] Lei Xue, Wang Lixue. Measurement Research on Expert Avoidance Relationship in Peer Review Based on Academic Relationship [J]. *Modern Information*, 2017, 37(3): 32-34.

[16] Wang Xianhui, Yuan Junpeng. A Peer Review Method for Social Relationships [J]. *Science and Technology Management Research*, 2017(23): 228-232.

[17] Li Jiang, Li Dong, Feng Peihua, et al. Research on Expert Recommendation Model Based on Expertise Matching Degree, Academic Influence and Social Association Value [J]. *Journal of the China Society for Scientific and Technical Information*, 2017, 36(4): 338-347.

[18] Zhao Liming, Xu Xiaohan, Zhang Weidong. Indicator System for Selecting Peer Review Experts [J]. *Scientific Research Management*, 1994(6): 17-21.

[19] Ma Xiaoguang, Lian Yanhua, Shen Quanfeng, Yu Hao. Research on Expert Identification in Peer Review [J]. *R&D Management*, 2003(3): 68-72.

[20] Chen Yuan, Fan Zhiping, Xie Meiping. Research on Evaluation of Peer Review Expert Level for Scientific Research Projects [J]. *Science of Science and Management of S.&T.*, 2009, 30(10): 38-42.

[21] Zhou Jianzhong, Xu Fang. Comparative Study on Peer Review Methods of National Research Institutions [J]. *Studies in Science of Science*, 2013, 31(11): 1642-1648.

[22] Salton G. *Introduction to modern information retrieval* [M]. New York: McGraw-Hill, 1983: 104.

[23] Chen Yunwei, Deng Yong, Chen Fang, et al. Research on Construction and Application of Composite Cooperation Intensity Index [J]. *Library and Information Service*, 2015, 59(13): 96-103.

[24] He Xiaoyu. Research on Credit Evaluation Model of Science and Technology Project Review Experts Based on TOPSIS [J]. Science and Technology Management Research, 2020, 40(3): 32-38.

[25] Yu Liping, Pan Yuntao, Wu Yishan. Research on Modified TOPSIS and Its Application in Science and Technology Evaluation [J]. Journal of Intelligence, 2012, 31(6): 103-107.

## Author Contributions

Dai Shiyu: Literature review, data collection and analysis, writing and revising the manuscript;

Shi Jin: Proposed the research framework, manuscript revision and review;

Li Ming: Manuscript revision and review.

---

## Research on Expert Avoidance Model of Scientific Research Projects Based on Paper Cooperation Relationship

Dai Shiyu, Shi Jin, Li Ming

School of Information Management, Nanjing University, Nanjing 210023

**Abstract:** [Purpose/significance] Aiming at the avoidance problem in the selection of peer review experts for scientific research projects, this paper attempts to propose a set of feasible model methods to determine avoidance experts, avoid the interference of interpersonal relationships in evaluation work, and ensure the standardization and fairness of scientific research evaluation. [Method/process] Firstly, the paper cooperation relationship between experts and applicants was taken as the entry point, with cooperation intensity, co-author depth, direction matching degree and review performance as the main indicators. Then, the comprehensive weight and modified TOPSIS were used to analyze each index, and the quantitative model of expert avoidance for scientific research projects was constructed. Finally, according to the specified number of expert group members, considering the distribution of age, institution, gender, etc., the experts who should be avoided were identified. [Result/conclusion] Through case analysis, it is found that this model can effectively avoid the problem of “only cooperation theory” when giving the list of avoidance experts, and has sufficient reasons for avoidance, which meets the requirements of the Ministry of Science and Technology Management for expert selection, and can provide certain decision support for expert selection.

**Keywords:** paper cooperation relationship; expert avoidance model; modified TOPSIS; scientific research projects

*Note: Figure translations are in progress. See original paper for figures.*

*Source: ChinaXiv — Machine translation. Verify with original.*